ICP Series on Climate Change Impacts, Adaptation, and Mitigation – Vol. 3

HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS

The Agricultural Model Intercomparison and Improvement Project
Integrated Crop and Economic Assessments, Part 1

editors
Cynthia Rosenzweig and Daniel Hillel

Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America

Imperial College Press

VISIT…

How to go to your page

This eBook contains Two Parts. It contains an Index at the end of each Part.

The front matter and content of each book have their own page numbering scheme, consisting of a part number and a page number, separated by a Colon.

For example, to go to page 18 of Part 1, type “1:18” in the "page #" box at the top of the screen and click "Go."

To go to page “123” of Part 2, type “2:123” or to go to page “vii” of Part 1, type “1:vii” ……and so forth.

Please refer to the eTOC for further clarification.

HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS

The Agricultural Model Intercomparison and Improvement Project Integrated Crop and Economic Assessments, Part 1

Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America

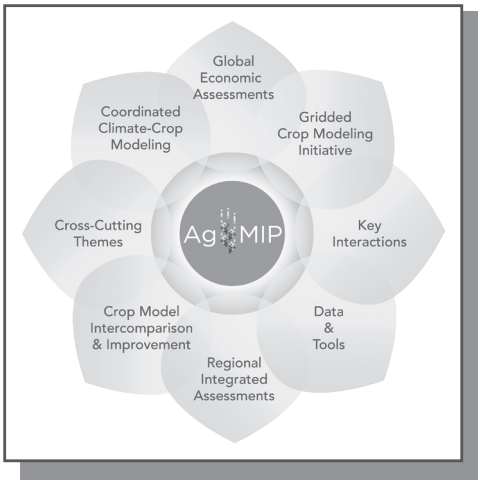
ICP Series on Climate Change Impacts, Adaptation, and Mitigation

Editors-in-Chief: Daniel Hillel and Cynthia Rosenzweig
(Columbia Univ. and Goddard Institute for Space Studies, USA)

Vol. 1: Handbook of Climate Change and Agroecosystems: Impacts, Adaptation, and Mitigation
edited by Daniel Hillel and Cynthia Rosenzweig

Vol. 2: Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications — Joint Publication with the American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America
edited by Daniel Hillel and Cynthia Rosenzweig

Vol. 3: Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments — Joint Publication with the American Society of America, and Soil Science Society of America
(In 2 Parts)
edited by Daniel Hillel and Cynthia Rosenzweig



ICP Series on Climate Change Impacts, Adaptation, and Mitigation – Vol. 3

HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS

The Agricultural Model Intercomparison and Improvement Project
Integrated Crop and Economic Assessments, Part 1

editors

Cynthia Rosenzweig
Daniel Hillel

Columbia University, Center for Climate Systems Research, USA

Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America

American Society of Agronomy | Crop Science Society of America | Soil Science Society of America

ICP

Imperial College Press

Published by

Imperial College Press
57 Shelton Street
Covent Garden
London WC2H 9HE

Distributed by

World Scientific Publishing Co. Pte. Ltd.
5 Toh Tuck Link, Singapore 596224
USA office: 27 Warren Street, Suite 401-402, Hackensack, NJ 07601
UK office: 57 Shelton Street, Covent Garden, London WC2H 9HE

British Library Cataloguing-in-Publication Data
A catalogue record for this book is available from the British Library.

ICP Series on Climate Change Impacts, Adaptation, and Mitigation — Vol. 3
HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS
The Agricultural Model Intercomparison and Improvement Project (AgMIP)
Integrated Crop and Economic Assessments — Joint Publication with the American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America
(In 2 Parts)

Copyright © 2015 by Imperial College Press

All rights reserved. This book, or parts thereof, may not be reproduced in any form or by any means, electronic or mechanical, including photocopying, recording or any information storage and retrieval system now known or to be invented, without written permission from the Publisher.

For photocopying of material in this volume, please pay a copying fee through the Copyright Clearance Center, Inc., 222 Rosewood Drive, Danvers, MA 01923, USA. In this case permission to photocopy is not required from the publisher.

ISBN 978-1-78326-563-3 (Set)
ISBN 978-1-78326-566-4 (Part 1)
ISBN 978-1-78326-567-1 (Part 2)

Typeset by Stallion Press
Email: enquiries@stallionpress.com

Printed in Singapore

In memory of Dr. Nadine Brisson
(1963–2011)

Dr. Brisson was the leader of the AgMIP Maize Pilot Study and an authority in developing tools to analyze the vulnerability of agricultural systems to climate change. She is remembered around the world for her expertise in crop modeling as well as for her energy, enthusiasm, and commitment to the advancement of agricultural knowledge and understanding for researchers, practitioners, policymakers, and educators. Her brilliant mind and shining spirit are missed by us all.

This page intentionally left blank

Foreword

Though past research has studied temperature and CO_2 effects on crop production, most of it has been done at the disciplinary level, and has not fully utilized an integrated multi-disciplinary approach, with experts in crop and soil sciences, together with agronomists, computer modelers, economists, climatologists, and others working in conjunction. This is the unique research program that AgMIP (the Agricultural Model Intercomparison and Improvement Project) has developed, seeking a voluntary from-the-ground-up approach to advance the field of agriculture as already impacted, and to be further impacted, by climate change.

An imperative task of our time is to develop and implement agricultural practices that can provide the food needed for the anticipated rise in the world's population to around 9 billion in the coming decades, and to do so sustainably without disrupting the remaining natural environment, its ecosystems, and its biota. Much of the debate on meeting future food production goals focuses on expansion of the land area for agriculture and/or intensified crop production on existing agricultural lands. Whereas there is no doubt that concern will focus on the availability of land suitable for agriculture and on improved soil, crop, and water management practices, uncertainty remains concerning the impacts of climate change on crop production. This includes the impacts of rising temperature and atmospheric CO_2 concentration, as well as potential increases in the frequency and intensity of droughts and floods.

The American Society of Agronomy (ASA), Crop Science Society of America (CSSA), and Soil Science Society of America (SSSA) have served as the scientific organizations to host the AgMIP scientists at their 2013 Tampa Annual Meeting, and to be part of this joint publication with Imperial College Press (ICP) on Climate Impacts, Adaptation, and Mitigation. We are especially proud of this volume being dedicated to developing, less-productive regions of Sub-Saharan Africa and South Asia, which are especially affected, and yet have the least information available regarding the portending effects on their major crops.

Related discussion is focused on concepts of "climate-smart agriculture". These concepts are called the "triple-win" approach, consisting of *increasing crop production* with improved agronomic practices, while *adapting to changing climate* and *reducing greenhouse gas emissions*. There is not likely to be a single solution for climate-smart agriculture, as management practices will be regionally determined

to accomplish this triple win, while sustaining soil health and productivity. This is clear from the global and regional assessments presented in this volume. AgMIP is a prime example of developing an integrated approach involving scientists and stakeholders to achieve food security, respond to climate changes, and reduce the scourges of poverty and hunger.

To achieve the triple win within the context of climate change will require much-needed innovative and integrated research such as developed by AgMIP. We congratulate its founders, editors, and contributing scientists on this unique assessment of climate change impacts and the reporting of ongoing regional activities. There is no doubt that these ongoing activities will have a major influence on the management of future agricultural systems under climate change.

Jan W. Hopmans

President, Soil Science Society of America

David B. Mengel

President, Agronomy Society of America

David Baltensperger

President, Crop Science Society of America
Madison, Wisconsin, 2014

Foreword

The *Handbook on Climate Change and Agroecosystems* produced by the scientists of the Agricultural Model Intercomparison and Improvement Project (AgMIP) is a key contribution to a sustainable food and agricultural system in the coming decades. Top agricultural scientists from around the world have taken up the challenge of sustainable agriculture, with the specific focus on integrating agronomic, climatological, biophysical and socio-economic perspectives and processes. Every chapter contributes to addressing the growing food-security challenges facing the world.

The food challenge is profound and complex for four interconnected reasons. First, the rising global population requires rising food production. Second, the pervasive challenges of poor nutrition, ranging from hunger to obesity, demands healthier diets. Third, the adverse environmental effects of farming — including freshwater depletion, loss of biodiversity, pollution, and greenhouse gas emissions — must be reduced. And fourth, the food system is profoundly threatened by the human-induced climate change now underway.

No single study, of course, can examine these profound and interconnected challenges. Indeed the scientific bases for understanding the complex linkages of farming, nutrition, human health, and environmental sustainability, are still being pieced together. This study makes a major, indeed fundamental, contribution to our understanding of the challenges of climate change for the future of agricultural systems around the world.

AgMIP is a unique international collaborative effort to assess the state of global and regional agricultural modeling and specifically to understand the impacts of climate and climate change on the agricultural sector. AgMIP's mission is to improve substantially the characterization of world food security as affected by climate variability and change, and thereby to enhance the capacity of both developing and developed countries to adapt to climate change in future years. AgMIP has grown into a global community of science, with over 700 members from over 40 countries.

The goal of this two-part study is to advance the field by providing detailed information on new simulation techniques and assessments being conducted by AgMIP. Leading international researchers from across the world have come together to develop improved methods for projecting climate change impacts, adaptation, and mitigation. AgMIP methods and results were cited multiple times in the "Food

Security and Food Production Systems" chapter of the IPCC Working Group II Fifth Assessment Report.

A special focus of the Handbook are the AgMIP integrated assessments that were carried out in Sub-Saharan Africa and South Asia from 2011 to 2014 by teams in the region, with major funding from the UK Department for International Development. These regions are among the most vulnerable in the world, and deserve AgMIP's concerted attention.

Over 200 agricultural scientists from around the world, representing a diverse group of developing and developed countries, have collaborated on this AgMIP contribution to the *Handbook on Climate Change and Agroecosystems*. The work is an essential contribution for regional, national, and international agricultural decision-makers who must develop sustainable agricultural systems in a time of accelerating climate change. The scientists who have contributed to this effort merit our deep thanks and appreciation for taking on this challenge of such global significance, and for bringing the best of the world's agronomic, economic, and climatological knowledge to bear in such a useful and comprehensive way.

Jeffrey D. Sachs

Director of the Earth Institute at Columbia University

Special Advisor to UN Secretary General Ban Ki-Moon on the Sustainable Development Goals

Preface

The potential effects of climate change on the food production system are raising concern both globally and regionally. The system is already challenged to deliver sufficient and healthy sustenance to all people, and is certain to be even further challenged as world population grows and price shocks loom. The prospect of climate change intensifies these challenges, raising the risk that more frequent and intense extreme weather events threaten the stability of agricultural production in regions around the globe.

This two-part set is an important contribution to the ongoing Imperial College Press (ICP) Series on Climate Change Impacts, Adaptation, and Mitigation. This series aims to provide the knowledge base necessary for understanding and responding to climate change, in both its current form and future manifestations. In these volumes, leading agricultural researchers have come together to contribute their expertise on actual and potential climate change impacts, adaptation strategies, and mitigation efforts.

This ongoing series is jointly published by The American Society of Agronomy (ASA), Crop Science Society of America (CSSA), and Soil Science Society of America (SSSA), together with ICP. We hope that this fruitful cooperation will continue for many years to come, as it spurs the global effort to define and meet the great food security and climate change challenges of our time.

Cynthia Rosenzweig and Daniel Hillel, Editors

This page intentionally left blank

About the Editors

Cynthia Rosenzweig is a leader in the field of climate change impacts. She is a senior research scientist at Columbia University's Center for Climate Systems Research and a professor in the Department of Environmental Science at Bernard College. She is also a senior research scientist at the NASA Goddard Institute for Space Studies, where she heads the Climate Impacts Group. She is the co-founder of the Agricultural Model Intercomparison and Improvement Project (AgMIP), a major international collaboration to improve global agricultural modeling, understand climate impacts on the agricultural sector, and enhance adaptation capacity in developing and developed countries. She was a coordinating lead author on observed climate change impacts for the IPCC Working Group II Fourth Assessment. She was named as one of *Nature*'s " Ten People Who Mattered in 2012". A recipient of a Guggenheim Fellowship, she joins impact models with climate models to project future outcomes under altered climate conditions.

Daniel Hillel is a world-renowned environmental scientist and hydrologist. He has worked in over 30 countries across North and South America, Europe, Asia, Africa, and Australia, with a major focus on the Middle East, where he served as a consultant to the governments of Israel, Pakistan, the Sudan, Iran, Egypt, Jordan, and Cyprus. He has worked as advisor to the World Bank and to the United Nations. His innovative techniques in soil and water management have ameliorated the daily lives of the rural citizens of these countries and of countries on all continents. He was awarded the 2012 World Food Prize for his role in conceiving and implementing micro-irrigation, a radically new mode of bringing water to crops in arid and dryland regions. He has published over 300 scientific papers and manuals on agriculture, the environment, climate change, and water-use efficiency, as well as authored or edited 24 books. These have been adopted by many universities as standard teaching and reference textbooks and translated into ten languages.

This page intentionally left blank

Acknowledgments

We especially acknowledge the late Mr. Mark Mandelbaum, the director of publications at ASA/SSSA/CSSA, for his role in bringing this joint project to fruition. He was passionate in disseminating science and technology research to the widest possible readership.

We thank Dr. Zvi Ruder, senior executive editor on behalf of Imperial College Press at World Scientific Publishing, for sharing the wisdom of his lifelong experience in publishing, and we thank Thomas Stottor, editor at Imperial College Press, for his expert and collegial preparation of this book for publication.

We thank Mr. Erik Mencos for his excellent and tireless assistance throughout the entire process of developing the Handbook. We thank Dr. Carolyn Mutter, Dr. Alexander Ruane, Dr. Angela Kong, Dr. Joshua Elliott, Dr. Jeffrey White, Dr. Cesar Izaurralde, Mr. Nicholas Hudson, and Ms. Monica Morales for their chapter reviews. Special acknowledgment is due to Dr. Sonali McDermid for her work on the South Asia and Southern India chapters and to Dr. Roberto Valdivia for his work on economics with the regional research teams. We are very grateful to Ms. Shari Lifson for her preparation of the graphics and final check for the entire volume and to Mr. Roberto Tinella for his assistance with the diagrams and figures.

We are grateful to all of our colleagues from the international agricultural research community who have helped to create AgMIP since its inception and those who are participating in current AgMIP activities. We appreciate especially the guidance provided by the AgMIP Principal Investigators and Steering Group.

Finally, we thank the UK Department for International Development; the United States Department of Agriculture; the CGIAR Research Program on Climate Change, Agriculture and Food Security; the United States Agency for International Development; and the National Aeronautics and Space Administration for their support of AgMIP.

This page intentionally left blank

Contents

Foreword, Jan W. Hopmans, David B. Mengel, and David Baltensperger vii

Foreword, Jeffrey D. Sachs ix

Preface xi

About the Editors xiii

Acknowledgments xv

Introduction The Role of the Agricultural Model Intercomparison and Improvement Project xxiii
Cynthia Rosenzweig and Daniel Hillel

Introduction to Part 1 xxvii

Section I. Overview of AgMIP **1**

Chapter 1. The Agricultural Model Intercomparison and Improvement Project: Phase I Activities by a Global Community of Science 3
Cynthia Rosenzweig, James W. Jones, Jerry L. Hatfield, John M. Antle, Alexander C. Ruane, and Carolyn Z. Mutter

Section II. Methods of Regional Integrated Assessments **25**

Chapter 2. AgMIP's Transdisciplinary Agricultural Systems Approach to Regional Integrated Assessment of Climate Impacts, Vulnerability, and Adaptation 27

John M. Antle, Roberto O. Valdivia, Kenneth J. Boote, Sander Janssen, James W. Jones, Cheryl H. Porter, Cynthia Rosenzweig, Alexander C. Ruane, and Peter J. Thorburn

Chapter 3. AgMIP Climate Data and Scenarios for Integrated Assessment 45

Alexander C. Ruane, Jonathan M. Winter, Sonali P. McDermid, and Nicholas I. Hudson

Chapter 4. Cropping Systems Modeling in AgMIP: A New Protocol-Driven Approach for Regional Integrated Assessments 79

Peter J. Thorburn, Kenneth J. Boote, John N. G. Hargreaves, Perry L. Poulton, and James W. Jones

Chapter 5. Representative Agricultural Pathways and Scenarios for Regional Integrated Assessment of Climate Change Impacts, Vulnerability, and Adaptation 101

Roberto O. Valdivia, John M. Antle, Cynthia Rosenzweig, Alexander C. Ruane, Joost Vervoort, Muhammad Ashfaq, Ibrahima Hathie, Sabine Homann-Kee Tui, Richard Mulwa, Charles Nhemachena, Paramasivam Ponnusamy, Herath Rasnayaka, and Harbir Singh

Chapter 6. Data Interoperability Tools for Regional Integrated Assessments 147

Cheryl H. Porter, Chris Villalobos, Dean Holzworth, Roger Nelson, Jefffrey W. White, Ioannis N. Athanasiadis, Meng Zhang, Sander Janssen, Rob Knapen, James W. Jones, Kenneth J. Boote, John Hargreaves, and John M. Antle

Section III. Global Estimates of Climate Impacts on Agriculture 173

Chapter 7. The AgMIP GRIDded Crop Modeling Initiative (AgGRID) and the Global Gridded Crop Model Intercomparison (GGCMI) 175

Joshua Elliott and Christoph Müller

Chapter 8. The AgMIP Coordinated Climate-Crop Modeling Project (C3MP): Methods and Protocols 191

Sonali P. McDermid, Alexander C. Ruane, Cynthia Rosenzweig, Nicholas I. Hudson, Monica D. Morales, Prabodha Agalawatte, Shakeel Ahmad, L. R. Ahuja, Istiqlal Amien, Saseendran S. Anapalli, Jakarat Anothai, Senthold Asseng, Jody Biggs, Federico Bert, Patrick Bertuzzi, Virender S. Bhatia, Marco Bindi, Ian Broad, Davide Cammarano, Ramiro Carretero, Ashfaq Ahmad Chattha, Uran Chung, Stephanie Debats, Paola Deligios, Giacomo De Sanctis, Thanda Dhliwayo, Benjamin Dumont, Lyndon Estes, Frank Ewert, Roberto Ferrise, Thomas Gaiser, Guillermo Garcia, Sika Gbegbelegbe, Vellingiri Geethalakshmi, Edward Gerardeaux, Richard Goldberg, Brian Grant, Edgardo Guevara, Jonathan Hickman, Holger Hoffmann, Huanping Huang, Jamshad Hussain, Flavio Barbosa Justino, Asha S. Karunaratne, Ann-Kristin Koehler, Patrice K. Kouakou, Soora Naresh Kumar, Arunachalam Lakshmanan, Mark Lieffering, Xiaomao Lin, Qunying Luo, Graciela Magrin, Marco Mancini, Fabio Ricardo Marin, Anna Dalla Marta, Yuji Masutomi, Theodoros Mavromatis, Greg McLean, Santiago Meira, Monoranjan Mohanty, Marco Moriondo, Wajid Nasim, Lamyaa Negm, Francesca Orlando, Simone Orlandini, Isik Ozturk, Helena Maria Soares Pinto, Guillermo Podesta, Zhiming Qi, Johanna Ramarohetra, Muhammad Habib ur Rahman, Helene Raynal, Gabriel Rodriguez, Reimund Rötter, Vaishali Sharda, Lu Shuo, Ward Smith, Val Snow, Afshin Soltani,

K. Srinivas, Benjamin Sultan, Dillip Kumar Swain, Fulu Tao, Kindie Tesfaye, Maria I. Travasso, Giacomo Trombi, Alex Topaj, Eline Vanuytrecht, Federico E. Viscarra, Syed Aftab Wajid, Enli Wang, Hong Wang, Jing Wang, Erandika Wijekoon, Lee Byun-Woo, Yang Xiaoguang, Ban Ho Young, Jin I. Yun, Zhigan Zhao, and Lareef Zubair

Section IV. Building AgMIP Science **221**

Chapter 9. Uncertainty in Agricultural Impact Assessment 223

Daniel Wallach, Linda O. Mearns, Michael Rivington, John M. Antle, and Alexander C. Ruane

Chapter 10. Uncertainties in Scaling-Up Crop Models for Large-Area Climate Change Impact Assessments 261

Frank Ewert, Lenny G.J. van Bussel, Gang Zhao, Holger Hoffmann, Thomas Gaiser, Xenia Specka, Claas Nendel, Kurt-Christian Kersebaum, Carmen Sosa, Elisabet Lewan, Jagadeesh Yeluripati, Matthias Kuhnert, Fulu Tao, Reimund Rötter, Julie Constantin, Helene Raynal, Daniel Wallach, Edmar Teixeira, Balasz Grosz, Michaela Bach, Luca Doro, Pier Paolo Roggero, Zhigan Zhao, Enli Wang, Ralf Kiese, Edwin Haas, Henrik Eckersten, Giacomo Trombi, Marco Bindi, Christian Klein, Christian Biernath, Florian Heinlein, Eckart Priesack, Davide Cammarano, Senthold Asseng, Joshua Elliott, Michael Glotter, Bruno Basso, Guillermo A. Baigorria, Consuelo C. Romero, and Marco Moriondo

Chapter 11. Statistical Analysis of Large Simulated Yield Datasets for Studying Climate Change Effects 279

David Makowski, Senthold Asseng, Frank Ewert, Simona Bassu, Jean-Louis Durand, Pierre Martre, Myriam Adam, Pramod K. Aggarwal, Carlos Angulo, Christian Baron, Bruno Basso, Patrick Bertuzzi,

Christian Biernath, Hendrik Boogaard, Kenneth J. Boote, Nadine Brisson, Davide Cammarano, Andrew J. Challinor, Sjakk J. G. Conijn, Marc Corbeels, Delphine Deryng, Giacomo De Sanctis, Jordi Doltra, Sebastian Gayler, Richard Goldberg, Patricio Grassini, Jerry L. Hatfield, Lee Heng, Steven Hoek, Josh Hooker, Tony L. A. Hunt, Joachim Ingwersen, Cesar Izaurralde, Raymond E. E. Jongschaap, James W. Jones, Armen R. Kemanian, Christian Kersebaum, Soo-Hyung Kim, Jon Lizaso, Christoph Müller, Naresh S. Kumar, Claas Nendel, Garry J. O'Leary, Jorgen E. Olesen, Tom M. Osborne, Taru Palosuo, Maria V. Pravia, Eckart Priesack, Dominique Ripoche, Cynthia Rosenzweig, Alexander C. Ruane, Fredirico Sau, Mickhail A. Semenov, Iurii Shcherbak, Pasquale Steduto, Claudio Stöckle, Pierre Stratonovitch, Thilo Streck, Iwan Supit, Fulu Tao, Edmar I. Teixeira, Peter Thorburn, Denis Timlin, Maria Travasso, Reimund Rötter, Katharina Waha, Daniel Wallach, Jeffrey W. White, Jimmy R. Williams, and Joost Wolf

Chapter 12. Crop Diseases and Climate Change in the AgMIP Framework 297

Ariena H. C. van Bruggen, James W. Jones, Jose Mauricio C. Fernandes, Karen Garrett, and Kenneth J. Boote

Appendix 1. Guide for Regional Integrated Assessments: Handbook of Methods and Procedures, Version 5.1 331

Cynthia Rosenzweig, James W. Jones, Jerry L. Hatfield, John M. Antle, Alexander C. Ruane, Ken J. Boote, Peter J. Thorburn, Roberto O. Valdivia, Cheryl H. Porter, Sander Janssen, and Carolyn Z. Mutter

Appendix 2. Guide for Running AgMIP Climate Scenario Generation Tools with R in Windows, Version 2.3 387

Nicholas I. Hudson and Alexander C. Ruane

Appendix 3. Fourth Annual AgMIP Global Workshop Report 441
Shari Lifson and Carolyn Z. Mutter

Index 517

Introduction
The Role of the Agricultural Model Intercomparison and Improvement Project

Cynthia Rosenzweig and Daniel Hillel

Columbia University
and NASA Goddard Institute for Space Studies
New York, NY, USA
crr2@columbia.edu
dh244@columbia.edu

Climate impacts on agriculture are of increasing concern in both the scientific and policy communities because of the need to ensure food security for a growing population. A special challenge is posed by the changes in the frequency and intensity of heatwaves, droughts, and episodic rainstorms already underway in many parts of the world. Changes in production are directly linked to such variations in temperature and precipitation during the growing season, and often to offseason changes in weather affecting soil-water storage and availability to crops. This is not an isolated problem but one of both global and regional importance, because of impacts on the livelihoods of smallholder farmers as well as consequences for the world food trade system.

This two-part set — the *Agricultural Model Intercomparison and Improvement Project (AgMIP): Integrated Crop and Economic Assessments* — is the first to be entirely devoted to AgMIP (www.agmip.org). AgMIP is a major international research program focused on climate change and agriculture. The goal of the two parts is to advance the field by providing detailed information on new simulation techniques and assessments being conducted by this program. It presents information about new methods of global and regional integrated assessment, results from agricultural regions, and adaptation strategies for maintaining food security under changing climate conditions.

AgMIP was developed to formulate and evaluate agricultural models, intercompare them, improve their ability to predict climate change, and assess its

actual and projected impacts, using improved models at global and regional scales. AgMIP has grown into a global community of science, with over 700 members from over 40 countries. These books are an outcome of the AgMIP Symposium held at the Annual Meetings of the American Society of Agronomy (ASA), Soil Science Society of America (SSSA), and the Crop Science Society of America (CSSA) in Tampa, Florida, in October, 2013. They are a joint publication of Imperial College Press (ICP) with the ASA/SSSA/CSSA, and together constitute the fourth volume of the ICP Series on Climate Impacts, Adaptation, and Mitigation, as part of the *Handbook of Climate Change and Agroecosystems*. This partnership provides worldwide impact for the 25 chapters in the two parts, which represent the work of over 200 authors.

A special focus of the volume is the AgMIP regional integrated assessments that were carried out in Sub-Saharan Africa and South Asia from 2011 to 2014. With funding from the UK Department for International Development (DFID), AgMIP regional research teams (RRTs) have conducted integrated assessments to achieve new research results that can be compared across locations. The goal of this ongoing coordinated set of studies is to improve understanding of both biophysical and socio-economic impacts of climate change in agricultural regions of Sub-Saharan Africa and South Asia.

Part 1 of the two-part set presents AgMIP methods, global findings, and cross-cutting themes. Part 1, Section I begins with an overview of the global and regional activities of AgMIP since its inception in 2010. Part 1, Section II describes the new methods for regional integrated assessment of climate change impacts on agricultural systems that AgMIP has developed and tested with its partners in Sub-Saharan Africa and South Asia. This section includes chapters on the transdisciplinary regional integrated assessment approach, use of climate datasets and scenarios, crop modeling, representative agricultural pathways, and information technology. Part 1, Section III summarizes the AgMIP work on the impacts of climate change on agriculture at a global scale, including the AgGRID Global Gridded Crop Model Intercomparison (GGCMI) and the AgMIP Coordinated Climate-Crop Modeling Project (C3MP). Part 1, Section IV is entitled "Building AgMIP Science," and consists of chapters on uncertainty, statistical analyses, and crop diseases.

Appendices to Part 1 include the *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures*, the *Guide for Running AgMIP Climate Scenario Generation Tools with R*, and a report of the Fourth Annual AgMIP Global Workshop.

Part 2 of the two-part set presents results of the AgMIP regional integrated assessments, providing responses to three core questions: (1) What is the sensitivity of current agricultural production systems to climate change? (2) What is the impact of climate change on future agricultural production systems? and (3) What are the

benefits of climate change adaptation? Part 2, Section I describes in detail the regions and farming systems investigated in Sub-Saharan Africa, the interactions between the researchers conducting the climate change assessments and their regional stakeholders, the data and methods of study, and their results. Part 2, Section II reports on the methods, data, and results from the AgMIP regional integrated assessments in South Asia. Part 2, Section III highlights AgMIP regional activities in Brazil and China. Part 2 then describes AgMIP capacity-building and outreach activities, including training in multiple crop models and tools. Part 2 ends with a chapter on "Major Findings and Future Activities", providing an overview of the entire two-volume set and summarizing key research activities that need to be undertaken to advance knowledge of climate change impacts on agriculture.

Appendices to Part 2 include reports of workshops that were held as part of the UK DFID-sponsored AgMIP Project. Workshops focused on Multiple Crop Model Training, TOA-MD Economic Model Training, and Sub-Saharan Africa and South Asia Regional Integrated Assessments.

This book thus presents the achievements of AgMIP in advancing improved global and regional integrated assessments of the potential effects of climate change on food security and of potential adaptation strategies. Throughout, the book examines key issues including the potential for adaptive capacities of different regions — such as developing or introducing more heat- and drought-tolerant crop varieties, management methods for dealing with more extreme climate events, soil conservation and fertility enhancement, as well as better water-use efficiency. AgMIP is dedicated to improving the responses to climate change in the developing agricultural regions of the world, as they are projected to experience the greatest impacts of climate change and the greatest rates of population growth, thus exacerbating threats to food security.

We hope that agronomists, crop scientists, economists, soil scientists, climatologists, geographers, as well as policymakers will find these volumes to be useful. They are aimed at academic researchers and their students, as well as at industry researchers and practicing professionals who are working on the front lines to understand climate change impacts on farming systems, develop and test appropriate adaptation strategies, and improve agricultural models. Further, they can serve as texts in undergraduate and graduate, training, and workshop courses on agronomy, crops, and soils; regional economics; and global climate change in general.

We believe that readers will benefit especially from the definitive contributions to this two-part set of more than 200 leading scientists from many of the key agricultural regions of the world. These scientists have worked together to improve substantially global and regional integrated assessments of the potential effects of climate change on agriculture and food security. The global studies present rigorous intercomparison

techniques, while the detailed regional studies provide rich examples of exciting new multi-model methods for assessing climate change impacts on, and adaptation strategies for, smallholder farming systems, including crucial effects on livelihoods and poverty. A major goal of future AgMIP activities is to build on these efforts to conduct coordinated and comprehensive global and regional assessments of climate change and agriculture, so as to better understand how climate change will impact agriculture around the world, and how agriculture can best respond.

Introduction to Part 1

Part 1 of the two-part set, *The Agricultural Model Intercomparison and Improvement Project: Integrated Crop and Economic Assessments*, presents AgMIP methods, global findings, and cross-cutting themes. Part 1, Section I of the two-volume set begins with an overview of the global and regional activities of AgMIP since its inception in 2010. Part 1, Section II describes the new methods for regional integrated assessment of climate change impacts on agricultural systems that AgMIP has developed and tested with its partners in Sub-Saharan Africa and South Asia. This section includes chapters on the transdisciplinary regional integrated assessment approach, use of climate datasets and scenarios, crop modeling, representative agricultural pathways, and information technology. Part 1, Section III summarizes AgMIP work on the impacts of climate change on agriculture at a global scale, including the AgGRID Global Gridded Crop Model Intercomparison (GGCMI) and the AgMIP Coordinated Climate-Crop Modeling Project (C3MP). Part 1, Section IV is entitled "Building AgMIP Science" and consists of chapters on uncertainty, statistical analyses, and crop diseases.

Appendices to Part 1 include the *AgMIP Guide for Regional Integrated Assessments: Handbooks of Methods and Procedures*, the *Guide for Running AgMIP Climate Scenario Generation Tools with R*, and a report of the Fourth Annual AgMIP Global Workshop.

This page intentionally left blank

Section I

Overview of AgMIP

This page intentionally left blank

Chapter 1

The Agricultural Model Intercomparison and Improvement Project: Phase I Activities by a Global Community of Science

Cynthia Rosenzweig[1,2], James W. Jones[3], Jerry L. Hatfield[4], John M. Antle[5], Alexander C. Ruane[1], and Carolyn Z. Mutter[2]

[1]*NASA Goddard Institute for Space Studies, New York, NY, USA*

[2]*Columbia University, New York, NY, USA*

[3]*University of Florida, Gainesville, FL, USA*

[4]*United States Department of Agriculture, Agricultural Research Service, Ames, IA, USA*

[5]*Oregon State University, Corvallis, OR, USA*

Introduction

The Agricultural Model Intercomparison and Improvement Project (AgMIP) was founded in 2010. Its mission is to improve substantially the characterization of world food security as affected by climate variability and change, and to enhance adaptation capacity in both developing and developed countries.

The objectives of AgMIP are to:

- Incorporate state-of-the-art climate, crop/livestock, and agricultural economic model improvements into coordinated multi-model regional and global assessments of future climate impacts and adaptation and other key aspects of the food system.
- Utilize multiple models, scenarios, locations, crops/livestock, and participants to explore uncertainty and the impact of data and methodological choices.
- Collaborate with regional experts in agronomy, animal sciences, economics, and climate to build a strong basis for model applications, addressing key climate-related questions and sustainable intensification farming systems.

- Improve scientific and adaptive capacity in modeling for major agricultural regions in the developing and developed world, with a focus on vulnerable regions.
- Improve agricultural data and enhance data-sharing based on their intercomparison and evaluation using best scientific practices.
- Develop modeling frameworks to identify and evaluate promising adaptation technologies and policies and to prioritize strategies.

The AgMIP Community of Science

There are now over 700 members of the AgMIP global community of science. AgMIP has built a dynamic and innovative international community of agricultural researchers to enable more robust agricultural-sector decision-making from local to global scales. One of AgMIP's biggest successes has been its ability to demonstrate goodwill and honest collaboration across previously competing modeling groups, providing a productive space to undertake challenging research endeavors. AgMIP Global Workshops anchor this community and facilitate collaboration to set agendas, design protocols for AgMIP activities, and encourage in-kind contributions to unravel the most difficult challenges in food-security modeling. Attendance at AgMIP's Global Workshops has risen by an average of ∼50% each year, with 250 participants at the latest workshop held in 2013. AgMIP also maintains a project listserve and website featuring information and tools for the scientific and lay public (Fig. 1) (www.agmip.org).

International AgMIP community activities are designed to further the mission of AgMIP toward conducting state-of-the-art assessments of climate impacts on food security at local, regional, and global scales. Among other functions, AgMIP maintains a science integration and coordination office at Columbia University in New York, conducts training on multiple crop and economic models, and creates information-technology tools.

Science Approach

Since 2010, AgMIP has engaged stakeholders and researchers to assess climate impacts on food security and plan for a more resilient future. AgMIP has built a cutting-edge assessment framework on both global and regional scales, which links climate, crops, livestock, and economics to help decision-makers better understand how climate change will reverberate through complex agricultural systems and markets. Prior to AgMIP, the majority of studies on the impacts of climate change on the agricultural sector utilized only a single crop model, did not address economic implications or the potential for adaptation, and featured methodological differences

Fig. 1. Screenshot of AgMIP website (www.agmip.org).

that severely limited comparison or aggregation of studies. AgMIP's approach eliminates these shortcomings and increases the rigor of scientific information that can aid in stakeholder decisions.

AgMIP brings together world leaders in climate, crop, livestock, and economic modeling to form the necessary framework to understand climate impacts on food security (Fig. 2) (Rosenzweig *et al.*, 2013b). That framework is based on a two-track science approach, with Track 1 focusing on model intercomparison and improvement, and Track 2 focusing on climate change multi-model assessment. Three cross-cutting science themes are *uncertainty*, *aggregation and scaling*, and *representative agricultural pathways* (RAPs; see Part 1, Chapter 5 in this volume). To accomplish this scientific approach, the work of the first phase of AgMIP was carried out by four teams: Climate, Crop Modeling, Economics, and Information Technology.

AgMIP Initiatives

AgMIP enables, supports, and provides oversight for a range of initiatives. These include (clockwise from top of Fig. 3) global economic assessments and global crop

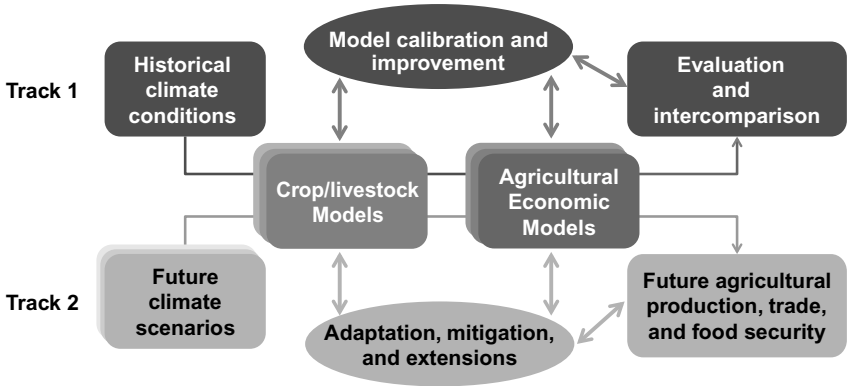


Fig. 2. AgMIP's dual scientific tracks create a robust framework capable of analyzing adaptation and policy decisions (from Rosenzweig *et al.*, 2013b).

modeling activities (via AgGRID; AgMIP GRIDded Crop Modeling Initiative), the development of next-generation models incorporating enhanced economic and environmental interactions, data and tools to facilitate multi-model and multi-discipline assessments, activities to understand and improve existing crop and livestock models, cross-cutting themes to help interpret agricultural model results for decision-making, and efforts to include the wider network of crop modelers around the world for future assessments (C3MP; Coordinated Climate-Crop Modeling Project).

To fulfill its mission, AgMIP is carrying out these initiatives on global and regional scales. Results from these initiatives contributed to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (e.g., Asseng *et al.*, 2013; Rosenzweig *et al.*, 2013a; Rosenzweig*et al*., 2013b; Müller and Robertson, 2013; Nelson *et al.*, 2013; Piontek *et al.*, 2013). They provide important context for national and regional stakeholders interpreting climate change risks, further state-of-the-art global food-security assessments and agricultural models, and deliver important inputs, such as commodity prices, into regional integrated assessments.

Crop model intercomparison and improvement

AgMIP's wheat, maize, rice, sugarcane, potato, livestock, and sorghum/millet teams were organized to test the robustness of crop model projections of climate impacts on agricultural production with a particular emphasis on intermodel uncertainty and validation against high-quality field data (Asseng *et al*., 2013; Bassu *et al*., 2014; Li *et al*., 2014). Each crop model intercomparison and improvement study selected a number of high-quality field sites, which ranged from partial information (to mimic data available at most locations) to nearly complete information levels

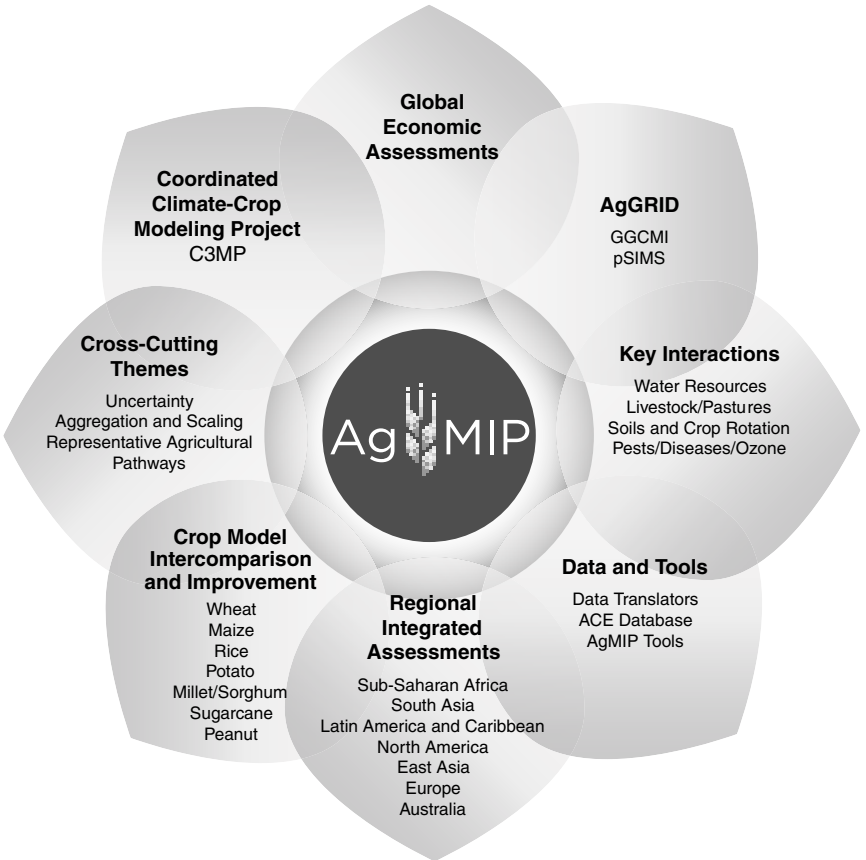


Fig. 3. AgMIP research and applications activities in support of integrated assessment of food security and agricultural impacts of climate change. GGCMI, Global Gridded Crop Model Intercomparison; pSIMS, Parallel System for Integrating Impact Models; ACE, AgMIP Crop Experiment database.

in order to gauge fundamental responses to temperature, rainfall, and CO_2 concentration changes. Each study includes sites in developing country regions, including Sub-Saharan Africa and South Asia, e.g., Delhi, India (wheat); Ludhiana, India (wheat); Morogoro, Tanzania (maize); La Mercy, South Africa (sugarcane); and Gisozi, Burundi (potato).

Figure 4 shows temperature and CO_2 responses from 27 models participating in the wheat model intercomparison, which reveal substantial intermodel uncertainties around a robust decline in yields with higher temperatures and increase in yields with higher CO_2 (Asseng *et al*., 2013). Intercomparisons such as these provide important information to stakeholders who must manage risk with access to only one or perhaps two sets of crop model results.

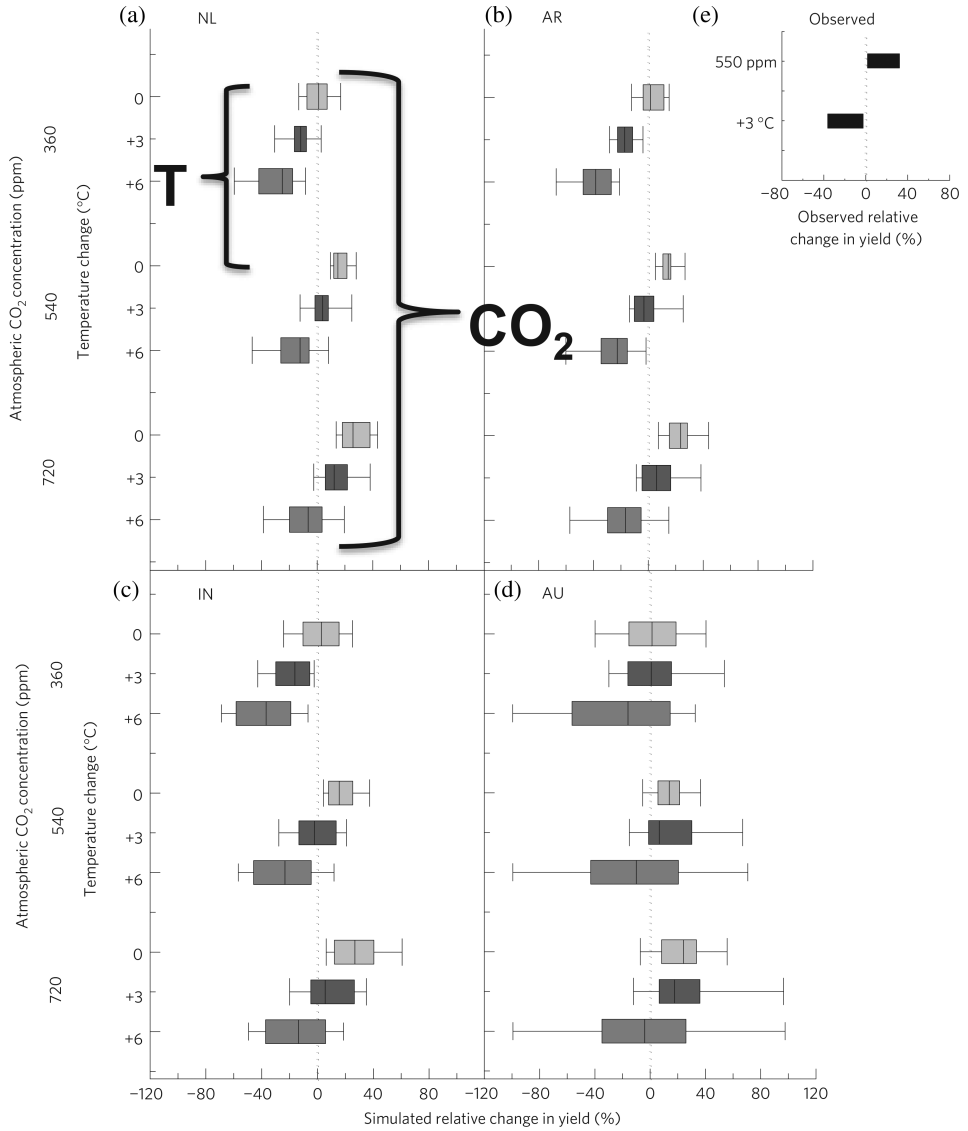


Fig. 4. Response of 27 wheat models to temperature (T) and CO_2 changes from the AgMIP wheat team. AR=Balcarce, Argentina; NL=Haarweg, the Netherlands; IN=Delhi, India; AU=Wongan Hills, Australia. From Asseng *et al.* (2013).

Coordinated Climate-Crop Modeling Project (C3MP)

AgMIP's Coordinated Climate-Crop Modeling Project (C3MP) engages with the world's crop modeling community, providing simple protocols and tools to assess fundamental climate responses on a diverse network of sites and crop models (Fig. 5).

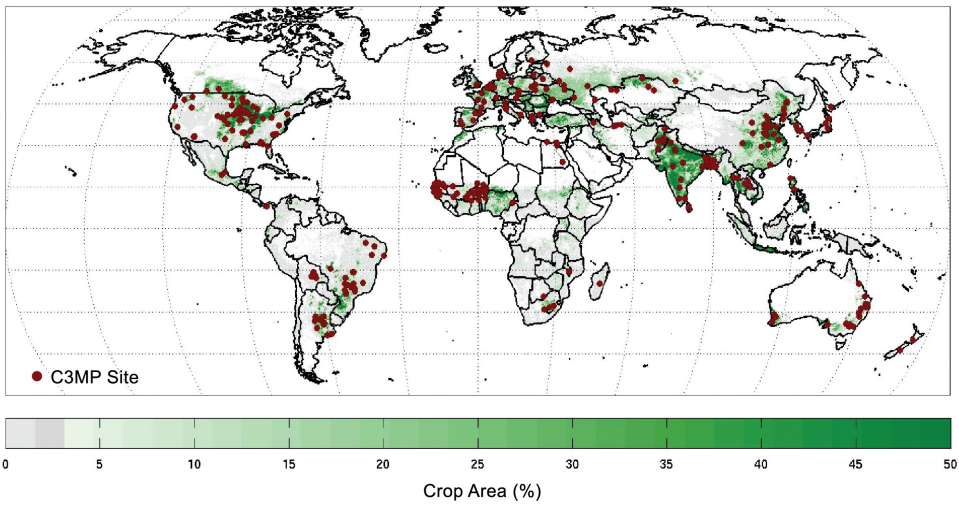


Fig. 5. C3MP model sites (dots) and major croplands (% area; green shading) as of January 24, 2014. (See Part 1, Chapter 8 in this volume.)

At present more than 100 participants have registered, with simulation sets contributed from 56 countries, 18 crops, and 23 crop models (see Part 1, Chapter 8 in this volume). Results are displayed on impact response surfaces that help stakeholders to visualize climate impacts.

C3MP aims to improve understanding of the impact of climate change on future agricultural production by utilizing site-calibrated crop models to coordinate projections of crop response under probabilistic climate change scenarios. Collaborations among crop modelers with expertise at specific modeling sites can provide improved estimates of how agricultural production will be impacted by climate change and can help assess how consistent these estimates are across climate and crop models. The results from C3MP will also contribute to wider assessments undertaken by AgMIP.

Through the C3MP protocols, crop modelers are invited to run a set of common climate sensitivity simulations, provided by C3MP coordinators, at sites where their models are already calibrated, and where detailed weather, cultivar, management, and soil information and data are available. Should weather information not be available, the C3MP coordinators provide a bias-adjusted MERRA (Modern-Era Retrospective Analysis for Research and Applications) weather time-series corresponding to the site (AgMERRA; Ruane *et al*., 2014). Modelers submit results via a template to the C3MP coordination team. The archived results are vetted and fit with an emulator to estimate yield response surfaces. These response surfaces may then be used to analyze the impacts of projected climate changes, beginning with the CMIP5 (Coupled Model Intercomparison Project Phase 5 (Taylor *et al*., 2012)) global climate models (GCMs).

AgGRID and Global Gridded Crop Model Intercomparison

AgGRID provides a central organizing hub for a new generation of gridded crop modeling activities within AgMIP, including the Global Gridded Crop Model Intercomparison (GGCMI). The goal is to build a lasting community of GGCMI researchers that collaborate to perform coordinated global and regional high-resolution impact assessments and model intercomparison studies. In turn, these improve GGCMI applications and understanding of climate impacts on global food production, as well as regional and temporal variations in these responses.

AgGRID leverages existing AgMIP strengths by bringing together AgMIP members from the climate, crop modeling, IT, economics, RAPs, aggregation and scaling, and uncertainty teams. Together, they develop new initiatives for improving quality and access to gridded data, models, computing, and scenario development and coalesce the international community of large-scale gridded crop modelers around important topics at the interface of food and climate.

The GGCMI facilitates a diverse international community of crop modelers to perform climate impact assessments, and to conduct model intercomparisons and improvements on the global scale. The GGCMI currently includes more than 15 modeling groups from nine countries. For those groups that have experience running models regionally, the project can provide the necessary data products and support to scale their existing frameworks up to global simulations. By working with the whole group, the coordination team establishes a consistent methodology, including simulation protocols and comparison metrics, for intercomparison and improvement of gridded model applications.

The coordination team also provides access to assimilated gridded environmental, socio-economic, and climate datasets, as well as all outputs and analyses to enable individual and collaborative studies within the GGCMI network. The GGCMI leverages resources and IT infrastructure (Earth System Grid Federation, Globus, etc.) developed at Argonne National Laboratory in Chicago, Illinois to facilitate data-sharing and discovery. This resource, which already serves 10 TB of climate and impact model outputs for the AgMIP and ISI-MIP (Inter-Sectoral Impact Model Intercomparison Project) communities (Warszawski *et al*., 2013), will be updated and managed as an ongoing resource for the impacts community for years to come.

In 2012, AgMIP led a GGCMI intercomparison fast-track project in coordination with ISI-MIP. This project included seven GGCMs and focused on updating the state-of-knowledge on climate change vulnerabilities, impacts, and adaptations using current climate model outputs (CMIP5). The fast-track project culminated with the publication of six papers in a special issue of the *Proceedings of the National Academy of Science of the United States of America*.

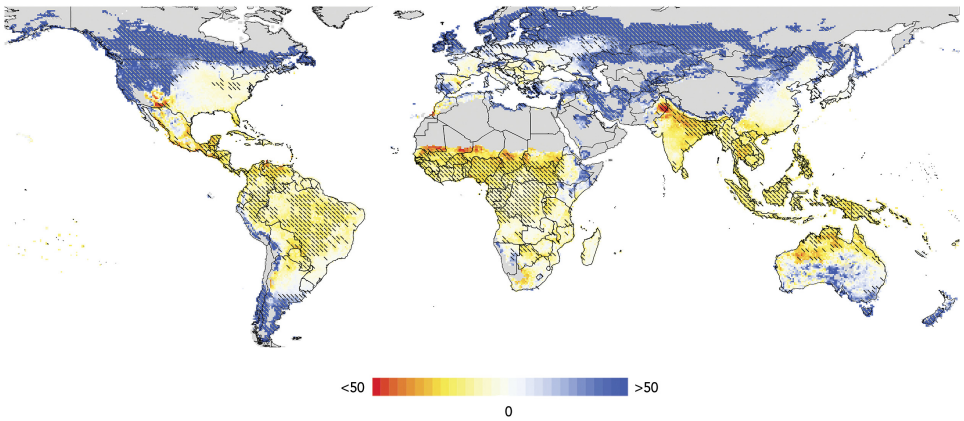


Fig. 6. Median end-of-century (2070–2099) maize yield changes (%; compared to 1980–2009 period) as simulated by seven global gridded crop models driven by five GCMs for RCP8.5. Hatching indicates regions where more than 70% of simulations had the same sign of maize yield changes (from Rosenzweig *et al.*, 2013a).

The intercomparison of seven global gridded crop models (GGCMs) analyzed climate impacts on maize, wheat, rice, and soybean across a global domain using high-performance computers (Fig. 6) (Rosenzweig *et al.*, 2013a). Crops in lower latitudes (including much of Sub-Saharan Africa and South Asia) demonstrate greater vulnerability as rising temperatures push cropping systems further from optimal conditions.

In contrast to previous assessments, results with realistic nitrogen fertilization show steadily decreasing yields for wheat, maize, and soybean in mid- and high-latitude regions even for small temperature increases. The design of the intercomparison allowed AgMIP to characterize uncertainty for the first time, highlighting the need for continuing rigorous model evaluation and improvement now being pursued in further phases of AgGRID. A new set of protocols for the next phase of the GGCMI, which focuses on data quality, harmonization, model evaluation, and improvement has been developed for five GCMs utilizing Representative Concentration Pathway 8.5 (RCP8.5) (Moss *et al.*, 2010).

Global economic assessments

AgMIP's Global Economic Model Intercomparison Team provided the first comprehensive investigation of uncertainty in projections of future commodity prices, agricultural land use, and agricultural gross domestic product (GDP). Climate change is projected to exert upward pressure on agricultural prices, but with large uncertainty (Fig. 7). Economies respond by eliminating poorly yielding areas (buffering overall yield declines), increasing agricultural land use, and reducing consumption

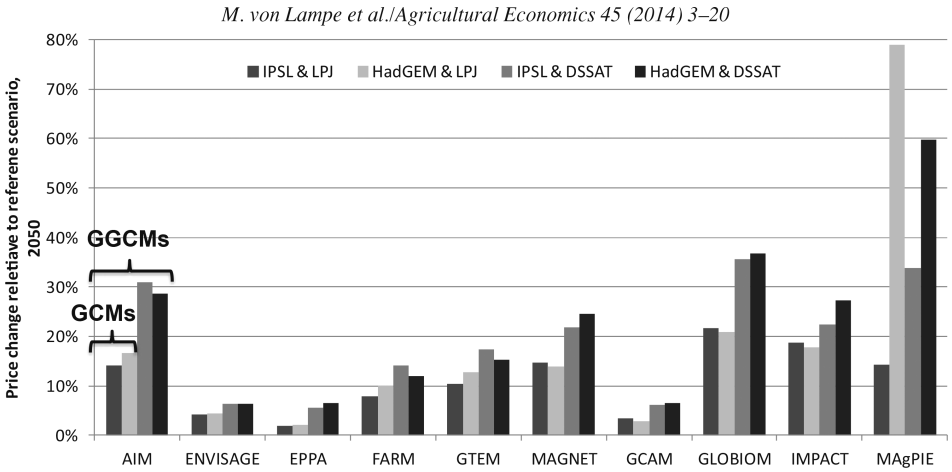


Fig. 7. Changes in world average producer prices for five main crops in 2050 due to climate change relative to no climate change. (Model results as of February 15, 2013.) *Note*: All changes relative to the reference scenario for the same year.

compared to the reference case with no climate change. While these reduce some of the detrimental impacts of climate change, there is still potential for large negative economic effects. Price uncertainties on the global market arise largely from the economic models, with smaller contributions from crop and climate models, although these can be substantial on the regional scale.

Comparisons between partial equilibrium (PE) models and computable general equilibrium (CGE) models revealed that the latter had a greater ability to buffer agricultural impacts through shifts in other economic sectors, but across all economic models projections were dependent on assumptions about the ease of land-use conversion, management intensification, and trade. Interactions within these models also shed light on how climate impacts drive economic responses; for example various countries take actions to reduce yield loss, increase crop area, and reduce consumption in the simulations.

Data and tools

The AgMIP IT team enables the compilation, archiving, and exchange of data and information for the AgMIP research community and stakeholders. The main objectives of the team are to develop an IT infrastructure for AgMIP projects that allows easy and secure access to shared data, models, and results of researchers in the AgMIP consortium, with both a short- and long-term perspective; facilitate the use of data by models and exchange of model results and the linking of models relevant for reproducible and repeatable applications; explore state-of-the-art information

and communications technologies relevant to improve agricultural modeling with a long-term perspective, including web-based model executions and service-oriented architecture (bio-informatics); and to organize the online dissemination of AgMIP data and outputs.

At the core of AgMIP is the use of multiple models for the purposes of quantifying model uncertainties and improving the performance of all participating models. The general categories of AgMIP tools that enable the multiple climate, crop, and economic models to be used for model intercomparisons and assessments are shown in Fig. 8.

One of the goals of AgMIP is the comparison of simulated results from various crop models for the purposes of quantifying model uncertainties and as a basis for model improvement. Multiple crop models are used to generate simulated estimates of crop yields and other data using identical input data for each model. However, the format of the input data varies among the models. Some models use text file inputs,

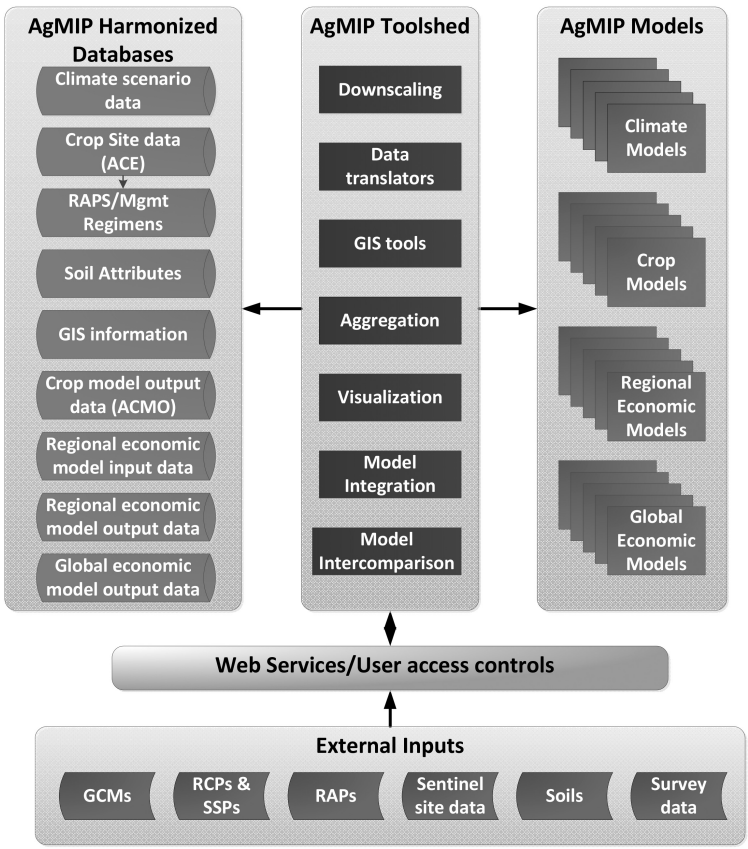


Fig. 8. AgMIP tools that enable multiple climate, crop, livestock, and economic models to be used for model intercomparisons and assessments.

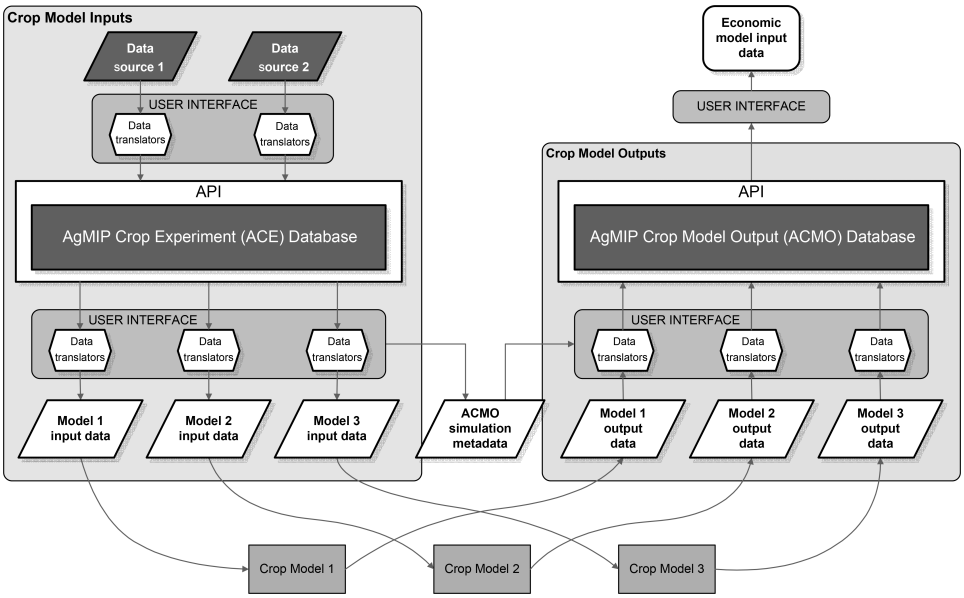


Fig. 9. AgMIP data-harmonization tools.

some use XML files, some use Excel spreadsheets, etc. Manual translation of data into the various model formats is not practical for the large amounts of data that are processed by AgMIP researchers.

To solve the problem, AgMIP stores crop experiment data in a harmonized data format and the harmonized data are exported to the formats specific to each model (Fig. 9). The AgMIP IT team has developed data translation tools to create the input data specific to each model. The AgMIP IT team works with the crop model development teams for each crop model to accomplish this goal. A series of development workshops have focused on programming the applications necessary for exporting data from the AgMIP harmonized crop experiment database to the data formats specific to each of the major crop models associated with AgMIP (see Part 1, Chapter 6 in this volume).

Regional Integrated Assessments

A major focus of AgMIP's activities in Phase 1 was the development of new methods for regional integrated assessments of climate change impacts on agricultural systems. The Sub-Saharan Africa and South Asia regional integrated assessments were organized into several distinct phases designed to create and execute a newly designed research and application agenda (Fig. 10).

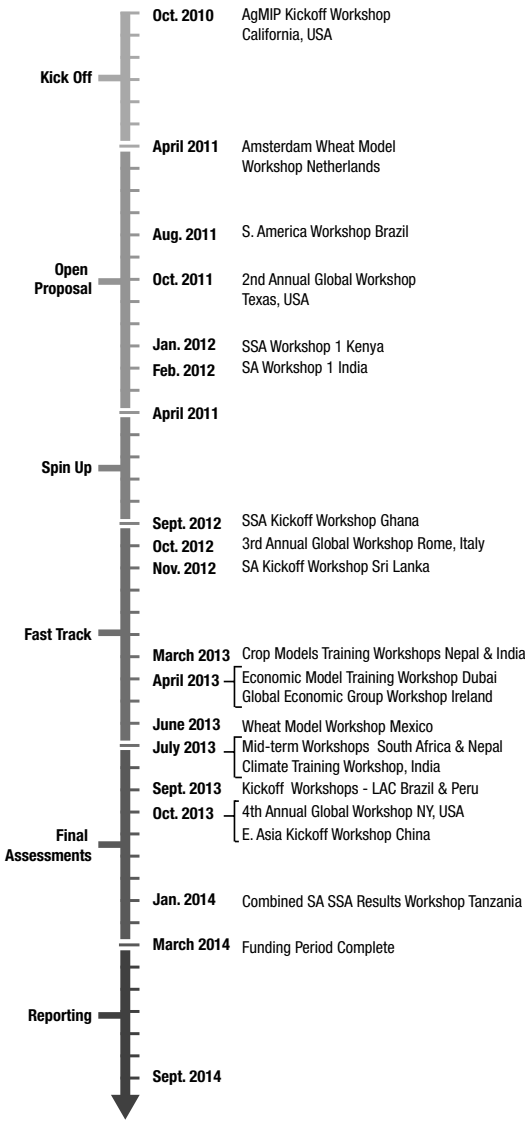


Fig. 10. Major project phases and project workshops for AgMIP Sub-Saharan and South Asia regional integrated assessments. For the report of the Fourth Annual Global Workshop see Appendix 3 in Part 1 of this volume.

AgMIP worked with regional research teams to conduct integrated assessments of climate impacts on the agricultural sector across Sub-Saharan Africa (with teams in East, West, Southern, and Southeastern Africa) and South Asia (with teams in the Indo-Gangetic Basin, Pakistan, Southern India, and Sri Lanka). These assessments developed and used innovative methods to understand how climate stresses

on production systems will affect agricultural productivity and livelihoods in diverse study regions (see Part 2, Chapters 1–10 in this volume).

As part of the project, the international network of AgMIP researchers built relationships with multiple groups of stakeholders, including national and regional agricultural planners, and demonstrated a transdisciplinary modeling framework to address specific questions related to adaptation investment and policy development. This community of stakeholders and researchers is now primed to carry out targeted evaluations of agricultural development and adaptation packages and to deliver results in a way that directly informs stakeholder and policymaker decisions as climate risks evolve.

Theory of change

AgMIP's theory of change drove researcher and stakeholder engagement throughout the project to ensure decision-relevant findings with development impact (Fig. 11). Key components of the AgMIP theory of change include:

- AgMIP develops the advanced multi-model framework for evaluating technologies and policies aimed at achieving development impacts.

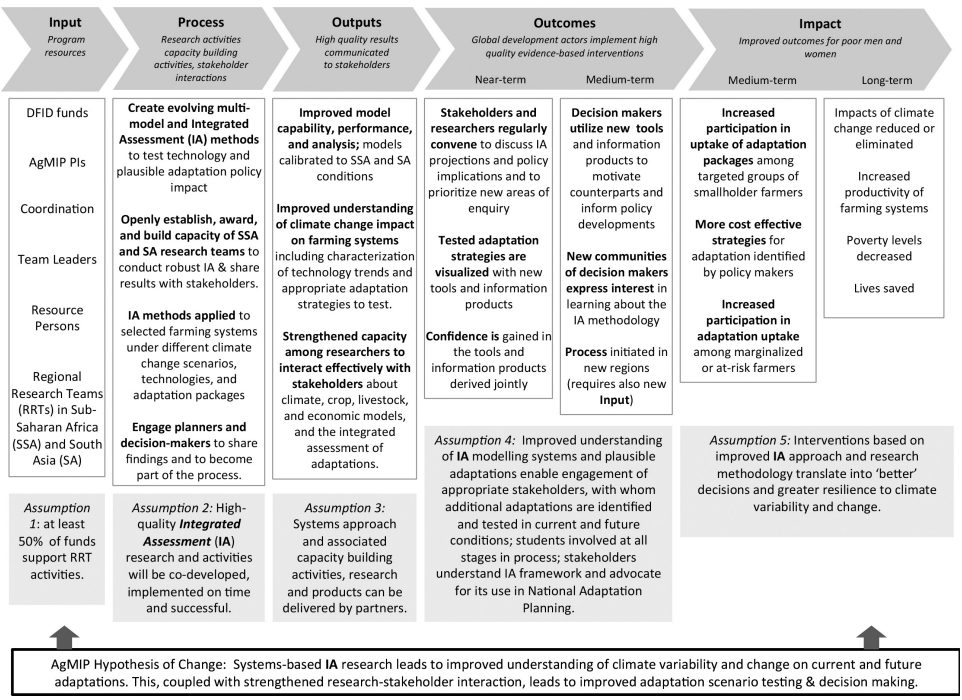


Fig. 11. The AgMIP theory of change.

- AgMIP helps regional researchers identify and engage appropriate stakeholders who provide critical links between research and development.
- AgMIP multi-disciplinary teams conduct regional integrated assessments and build regional capacity for effective use of the framework with stakeholders as partners.
- Stakeholders and researchers in the region adopt the AgMIP framework to achieve development impacts.

Stakeholder process

The selection of regional research teams included a criterion for stakeholder engagement, and each team met with stakeholders early in the project to prioritize regions and challenges for focused study. Stakeholders included representatives from agricultural ministries, farmer organizations, national and regional adaptation planners, crop breeders, non-governmental organizations, and extension agents. Stakeholders participated in each AgMIP workshop and also facilitated the dissemination of project information to the wider community.

Much of AgMIP's first phase was focused on developing the modeling framework and required capacity to conduct integrated assessment of policy options and adaptation packages, and a pilot of each was developed in consultation with regional stakeholders. Now that the multi-model framework is well established and a prototype application has been conducted in each region, stakeholder feedback from the final AgMIP Workshop provides a strong starting point for ongoing stakeholder engagement and co-exploration of policy and adaptation options in the next phase of AgMIP activities in Sub-Saharan Africa and South Asia.

Impact of AgMIP in Sub-Saharan Africa and South Asia (2010–2014)

On the regional scale, AgMIP enables decision-makers to have access to information that can be used to evaluate and prioritize climate change adaptation strategies for smallholder agricultural households. This information is based on rigorous new data and methods for climate impact and adaptation assessment on the local and regional scales relevant to decision-makers, and supported by regional research teams. These findings directly inform planning across a wide range of local, regional, national, and international stakeholders, many of whom have been involved via AgMIP's stakeholder-engagement process. Results have led to improved scientific capacity around the world.

AgMIP's innovative approach encompasses the range of smallholder households within a region, representing farm systems (e.g., including minor crops, livestock, labor, and off-farm income) and allowing more realistic analysis of adaptation

strategies including farm management, economic decisions, and regional policies. As opposed to the majority of previous studies that simulated a representative field with little recognition of heterogeneity and economic responses, AgMIP results offer a more practical projection of how climate change will affect different types of households, providing information about winners and losers in the face of climate and economic changes as well as those most likely to adopt proposed adaptation packages.

AgMIP assessments found that climate change adds pressure to smallholder farmers across Sub-Saharan Africa and South Asia, with winners and losers within each area studied. Temperatures are expected to increase in all locations, and rainfall decreases are projected for the western portion of West Africa and Southern Africa. Rainfall patterns are less certain in central West Africa and East Africa, although increases in rainfall are projected for eastern West Africa and all study regions of South Asia. Climate changes lead to yield decreases in most study regions except South India and areas in central Kenya, as detrimental temperature effects overcome the positive effects of CO_2. AgMIP researchers are examining the responses in multiple crop models to improve understanding of the nature of climate impacts and to inform the development of targeted adaptation packages.

Working with the input of regional stakeholders, AgMIP regional research teams developed and tested pilot climate change adaptation packages, finding that there is potential for partial compensation of yields as well as income and poverty metrics. Adaptations include relatively simple adjustments to management (e.g., shifts in planting date or plant populations) as well as decisions over a longer horizon including investments in water resources, agricultural subsidies, and new seed varieties.

AgMIP is creating a legacy through substantial gains in capacity achieved by African and South Asian climate scientists, agronomists, and economists, including women scientists and both junior and senior researchers. At the global scale, AgMIP has emerged as an international leader in the use of agricultural models for assessment of climate impacts on crop production, food security, economic development, and adaptation strategies.

AgMIP has built a network of researchers across the globe who conduct integrated analyses of climate change impacts on food security and agricultural economics. These researchers understand the importance of using multiple models and linking climate, crop, livestock, and economic models to examine both current and future agricultural systems as a distribution of households rather than a single block. Capacity gains included increased modeling experience for more than 200 participants, training of more than a dozen agronomists in a second crop model, improvements in regional economic modeling capacity, increased interactions with vital stakeholder communities, new capabilities for climate scenario generation,

and increased collaboration between scientists from different disciplines, countries, institutions, universities, genders, and seniority levels.

Major Achievements and Findings from AgMIP Phase 1

New methods

- Climate change impacts on food security, income, and poverty assessed for current farming systems and the types of farming systems that are likely to occur in the future, giving a more realistic projection of how climate change will facilitate or impede economic development.
- Future farming systems may be more capable of absorbing yield losses than the farming systems in current practice.
- First comprehensive regional integrated assessment of climate change impacts on smallholder farming systems in Sub-Saharan Africa and South Asia led by regional researchers and using best available data and multiple models.
- New methods integrating climate, crop, livestock, and economic models to conduct multi-model climate change impact assessments that characterize differential impacts on smallholder groups within a given region.
- Direct evaluation of yield, income, and poverty outcomes from pilot adaptation packages and development pathways.

Global assessments

- Crops in lower latitudes (where most developing countries are located) show greater vulnerability to climate change.
- In contrast to previous assessments that projected a period of increasing crop yields before temperature effects reduce yields, the AgMIP global gridded crop model results with realistic nitrogen fertilization show steadily decreasing yields for wheat, maize, and soybean in mid- and high-latitude regions even for small temperature increases (Rosenzweig *et al*., 2013a); this finding is backed up by an independent analysis conducted for the IPCC of individual climate impact studies (IPCC, 2014).
- Climate change is projected to exert upward pressure on global agricultural prices, but with large uncertainty. Price uncertainty on the global market comes largely from economic models, with smaller contributions from crop and climate model uncertainty, although these can be substantial on the regional scale. Economic models differ primarily in assumptions about ease of land use conversion, intensification, and trade.

- Economic systems respond to climate impacts by taking actions to reduce yield loss, increase crop area, and alter demand.

Regional assessments

AgMIP conducted the first set of comprehensive regional integrated assessments of climate change impacts on smallholder farmers in Sub-Saharan Africa and South Asia, led by researchers from the regions themselves. The project developed new methods integrating climate, crop, livestock, and economic models to conduct climate change impact assessments that characterize impacts on smallholder groups. AgMIP projections of climate change impacts on agriculture are more realistic than previous assessments because they take agricultural development into account. Using the best available data and models, the assessments directly evaluated yield, income, and poverty outcomes including the effects of adaptation packages and development pathways. The studies found that climate change will slow the pace of development in many current smallholder agricultural systems and that even in cases where average impact is near zero, vulnerability (i.e., those at risk of loss) can be substantial even when mean impacts are positive. See Part 2, Chapters 1–10 in this volume for further description of AgMIP regional assessments.

Sub-Saharan Africa

Agriculture in Sub-Saharan Africa (SSA) is already experiencing climate change-related effects that call for regional integrated assessments, yet capacity for these assessments has been low (see Part 2, Chapter 1 in this volume). AgMIP is advancing research on integrated regional assessments of climate change involving climate, crop, and economic modeling and analysis. Through AgMIP, regional integrated assessments are increasingly gaining momentum in SSA, and multi-institutional regional research teams centered in Eastern, Western, and Southern Africa are generating new information on climate change impacts and adaptation in selected agricultural systems (see Part 2, Chapters 2–5 in this volume). Key findings include:

- Even with agricultural development, climate change generally will exert negative pressure on maize yields of smallholder farmers in SSA, ranging across the four different regions and systems assessed.
- Without adaptation, climate change leads to increased poverty in some locations in SSA compared to a future in which climate change does not occur.
- Adaptation can improve smallholder farmer responses to climate change in SSA.
- However, many farmers lack the capability to respond effectively to the increasing climate risks projected for their regions. Some smallholder farmers will gain from climate change, but most farmers will lose.

- In the four regions assessed, AgMIP expert teams identified improved varieties, sowing practices, fertilizer application, and irrigation applications as prioritized adaptations. These targeted adaptation packages were able to overcome a portion of detrimental impacts but could not compensate completely in many locations.

South Asia

Understanding the response of current agricultural production to climate variability and future climate change is of utmost importance to secure food and livelihoods for South Asia's growing population. AgMIP South Asian regional research teams undertook climate–crop–economic integrated assessments of food security for districts in these countries, with the goal of characterizing the state of food security and poverty across the region, and projecting how these are subject to change under future climate conditions (see Part 2, Chapters 7–10 in this volume). Key findings include (Fig. 12):

- Even with agricultural development, climate change generally will exert negative pressure on rice yields of smallholder farmers in South Asia.
- Without adaptation, climate change leads to increased poverty in many locations in South Asia compared to a future in which climate change does not occur.
- Adaptation can significantly improve smallholder farmer responses to climate change in South Asia for all but the smallest farm sizes.
- Many farmers lacked the capability to respond effectively to the increasing climate risks projected for their regions.
- In the four regions assessed, AgMIP expert teams identified improved varieties, sowing practices, fertilizer application, and irrigation applications as prioritized adaptations. These targeted adaptation packages were able to overcome a portion of detrimental impacts but could not compensate completely in many locations.

Evolving to the AgMIP Global Program

AgMIP has now launched regional projects on six continents and is building a global program to formalize collaboration and decision-making between AgMIP and regional leaders (Fig. 13). AgMIP's Science Integration and Coordination Office at Columbia University spearheads interactions with national agricultural ministries, international development agencies, and research teams, which in turn lead to interactions with stakeholders and decision-makers across multiple scales. Building on

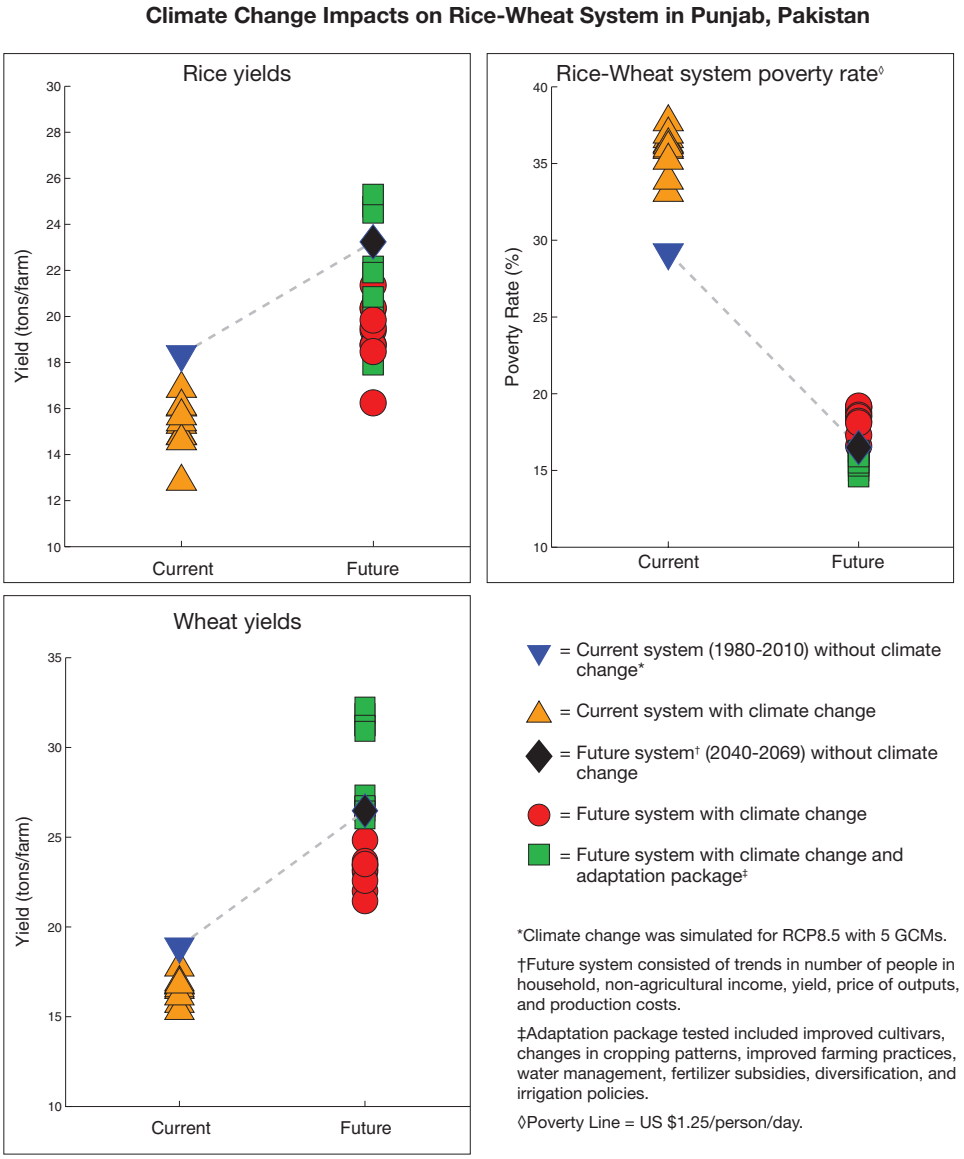


Fig. 12. Impacts of climate change on current and future rice-farming systems in the Punjab, Pakistan, with and without adaptation.

these interactions, AgMIP is organizing coordinated global and regional assessments of climate change impacts on the food system and the development of the next generation of agricultural models that can be used to develop and evaluate sustainable technologies.

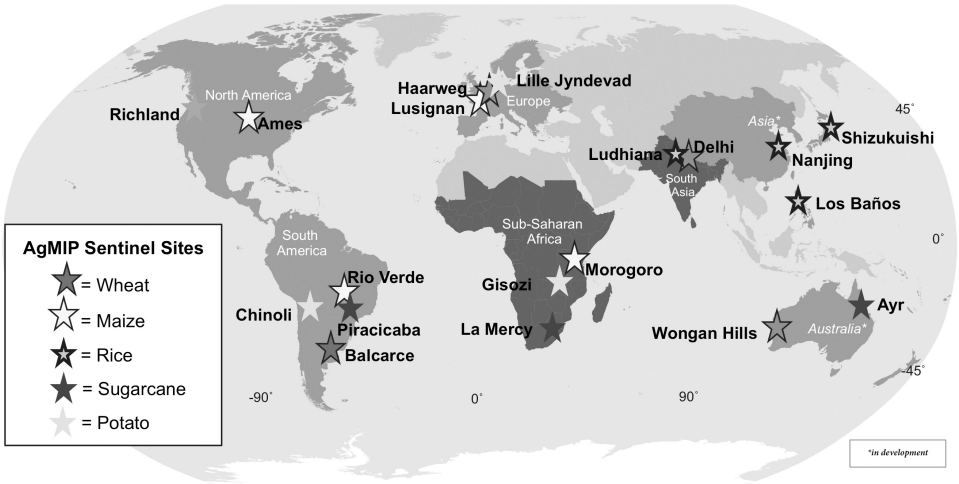


Fig. 13. AgMIP regional programs (darker tone indicates DFID-funded regions) and crop model intercomparison sites from Phase 1.

References

Asseng, S., Ewert, F., Rosenzweig, C. Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**(9), 827–832.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K. J., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J. L., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A., Kersebaum, K., Müller, C., Nendel, C., Priesack, E., Nin, M. V. P., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Makowski, D., Timlin, D., and Waha, K. (2014). Do various maize crop models give the same responses to climate change factors?, *Global Change Biology*, **20**, 2301–2320.

Cecil, L. D., Horton, R. M., Gordón, R., McCollum, R., Brown, D., Killough, B., Goldberg, R., Greeley, A. P., and Rosenzweig, C. (2013). Climate change impact uncertainties for maize in Panama: Farm information, climate projections, and yield sensitivities, *Agric. For. Meteorol.*, **170**, 132–145.

Intergovernmental Panel on Climate Change (IPCC) (2014). *Climate Change 2014: Impacts, Adaptation and Vulnerability*, IPCC Working Group II contributions to AR5.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J. Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

Müller, C. and Robertson, R. D. (2013). Projecting future crop productivity for global economic modeling, *Agric. Econ.*, **45**(1), 37–50.

Nelson, G. C., van der Mensbrugghe, D., Ahammad, H., van der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., von Lampe, M., d'Croz1, D. M., van Meijl, H., Müller, C., Reilly, J., Robertson, R., Sands, R. D., Schmitz, C., Tabeau, A., Takahashi, K., Valin, H., and Willenbockel, D. (2013). Agriculture and climate change in global scenarios: Why don't the models agree, *Agric. Econ.*, **45**(1), 85–101.

Piontek, F., Müller, C., Pugh, T. A. M., Clark, D. B., Deryng, D., Elliott, J., de Jesus Colón González, F., Flörke, M., Folberth, C., Franssen, W., Frieler, K., Friend, A. D., Gosling, S. M., Hemming, D., Khabarov, N., Kim, H., Lomas, M. R., Masaki, Y., Mengel, M., Morse, A., Neumann, K., Nishina, K., Ostberg, S., Pavlick, R., Ruane, A. C., Schewe, J., Schmid, E., Stacke, T., Tang, Q., Tessler, Z. D., Tompkins, A. M., Warszawski, L., Wisser, D., and Schellnhuber, H. J. (2013). Multisectoral climate impact hotspots in a warming world, *Proc. Natl. Acad. Sci. USA*, *(ISI-MIP Special Feature)*, **111**(9), 3233–3238.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., and Jones, J. W. (2013a). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison, *Proc. Natl. Acad. Sci. USA*, **111**(9), 3268–3273.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013b). The Agricultural Model Intercomparison And Improvement Project (AgMIP): Protocols and pilot studies, *Agric. For. Meteorol.*, **170**, 166–182.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design, *Bulletin of the American Meteorological Society*, **93**(4), 485–498.

von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., d'Croz, D. M., Nelson, G. C., Sands, R. D., Schmitz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., and van Meijl, H. (2014). Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison, *Agric. Econ.*, **45**(1), 3–20.

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., and Schewe, J. (2014). The Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP): Project framework, *Proceedings of the National Academy of Sciences*, **111**(9), 3228–3232.

Section II

Methods of Regional Integrated Assessments

This page intentionally left blank

Chapter 2

AgMIP's Transdisciplinary Agricultural Systems Approach to Regional Integrated Assessment of Climate Impacts, Vulnerability, and Adaptation

John M. Antle[1], Roberto O. Valdivia[1], Kenneth J. Boote[2], Sander Janssen[3], James W. Jones[2], Cheryl H. Porter[2], Cynthia Rosenzweig[4,5], Alexander C. Ruane[4], and Peter J. Thorburn[6]

[1]*Oregon State University, Corvallis, OR, USA*

[2]*University of Florida, Gainesville, FL, USA*

[3]*Wageningen University, Wageningen, the Netherlands*

[4]*NASA Goddard Institute for Space Studies, New York, NY, USA*

[5]*Columbia University, New York, NY, USA*

[6]*Commonwealth Scientific and Industrial Research Organization, Brisbane, Australia*

Introduction

This chapter describes methods developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP) to implement a transdisciplinary, systems-based approach for regional-scale (local to national) integrated assessment of agricultural systems under future climate, biophysical, and socio-economic conditions. These methods were used by the AgMIP regional research teams in Sub-Saharan Africa and South Asia to implement the analyses reported in their respective chapters of this book. Additional technical details for these methods are provided in Appendix 1: *Guide for Regional Integrated Assessments: Handbook of Methods and Procedures*, which is also available on the AgMIP website at http://agmip.org.

The principal goal that motivates AgMIP's regional integrated assessment (RIA) methodology is to provide scientifically rigorous information needed to support improved decision-making by various stakeholders, ranging from local to national and international non-governmental and governmental organizations. To meet this goal, through interactions with stakeholders and researchers, a number of key features of the approach were identified:

- A protocol approach must be used that is based on a rigorously documented methodology so that results can be replicated and intercompared, and so that methods can be improved over time.
- The study design must be made with input from stakeholders and policymakers, and include the systems and adaptations to be investigated, the future pathways and scenarios to be used in the assessments, and the identification of impact indicators to be used.
- A transdisciplinary, systems-based approach is needed that can incorporate important features of current and possible future systems, including multiple crops, inter-crops, livestock, and non-agricultural sources of income. The approach must provide a sufficient multi-climate level of detail about the production systems to allow meaningful characterization of possible adaptations.
- The approach must be able to account for the highly diverse types of systems, and the widely varying biophysical and socio-economic conditions that characterize farms.
- The approach must be able to incorporate the high degree of heterogeneity in biophysical and economic conditions typical of most agricultural regions.
- The methods must be able to quantify vulnerability to climate change in a meaningful way, i.e., it must be possible to characterize the impacts on those farm households that are adversely affected by climate change, as well as those that benefit from climate change. In other words, it must be possible to quantify not only average impacts but also the distribution of impacts in diverse populations.
- Key uncertainties in climate, crop, biophysical, and economic dimensions of the analysis must be assessed and reported so that decision-makers can understand them and use them to interpret the results of the analysis (see Part1, Chapters 9 and 10 in this volume).

Key Indicators and Core Climate Impact Questions

Based on discussions with stakeholders as well as the large body of research on climate change and its impacts, a number of key indicators were identified to assess impact, vulnerability, and adaptation, that are consistent with the key features

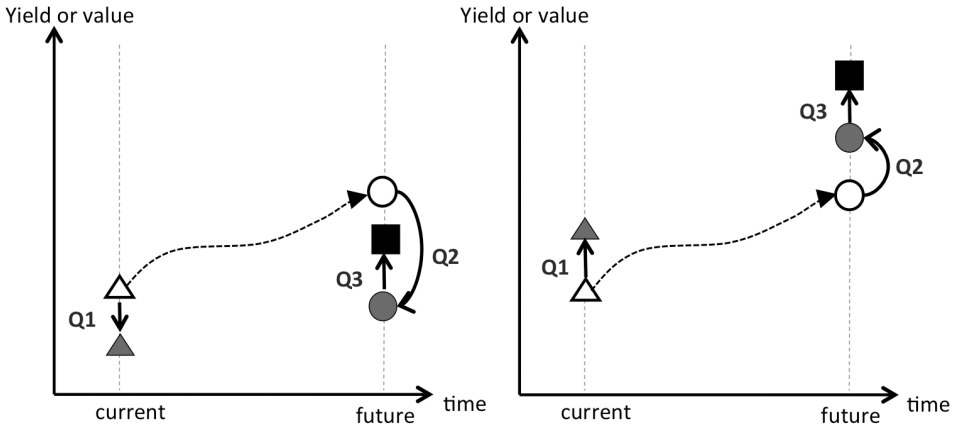
presented above:

- Changes in climate (temperature, precipitation, and carbon dioxide concentrations).
- Changes in average (or aggregate) physical production for principal production activities of the system, a key factor in regional and local food security.
- The proportion of households that are adversely affected by climate change through changes in the productivity of their agricultural system; a measure of the degree of vulnerability to climate change.
- The proportion of households that may benefit from climate change through changes in the productivity of their agricultural system; a measure of the size of the non-vulnerable population.
- Changes in average monetary value of the production system's outputs (an aggregate measure of the system's productivity) for losers and gainers, to indicate the magnitude of vulnerability as well as potential positive impacts.
- Average household *per capita* income; a measure of overall well-being, closely related to household food security.
- The headcount poverty rate in the population (i.e., the proportion of households below the poverty line); another key indicator of economic well-being for both vulnerable and non-vulnerable segments of the population.

The RIA methodology is designed to quantify the impacts of climate change on agricultural systems by using the above indicators. AgMIP has identified the following core research questions that allow the above indicators to be quantified in ways that support informed decision-making by various stakeholders (see Fig. 1):

Question 1. What is the sensitivity of current agricultural production systems to climate change? This question addresses the impacts of climate changes, assuming that the production system does not change from its current state under current biophysical and socio-economic conditions. While this type of analysis can provide some insights into potential impacts, its relevance is limited because of the use of current socio-economic conditions to quantify impacts.

Question 2. What is the impact of climate change on future agricultural production systems? This question evaluates the impacts of climate change on the production system that is projected for a future world without climate change. In contrast to the analysis done for Question 1, the analysis is carried out under biophysical and socio-economic conditions projected into the future with and without climate changes. This type of analysis is more relevant to understanding climate impacts and thus the potential benefits of adaptation, but is more challenging because all of the relevant variables affecting the systems must be projected into the future.



	System 1	System 2	Key Outputs
Question #1	△ Production system in **Current Period** with **Current climate**	▲ Production system in **Current Period** with **Future Climate**	***% gainers & losers and net impacts*** % change in mean farm income % change in per capita income % change in poverty rate
Question #2	○ Production system in **Future Period** with **Current climate** Productivity and price trends with no climate Change and RAPs	● Production system in **Future Period** with **Future Climate** Price trends with climate Change and RAPs	***% gainers & losers and net impacts*** % change in mean farm income % change in per capita income % change in poverty rate
Question #3	● Production system in **Future Period** with **Future Climate** Price trends with climate Change and RAPs	■ Adapted Production system in **Future Period** with **Future Climate** Price trends with climate Change, RAPs and Adaptation Package	***Adoption rate (%)*** % change in mean farm income % change in per capita income % change in poverty rate

Fig. 1. The three core questions for the case of negative (top, left) and positive (top, right) climate impacts.

Question 3. What are the benefits of climate change adaptations? This question addresses the design of adaptation options for the future production systems, the degree to which they would be likely to be adopted, and the economic, environmental, and social outcomes that would be associated with their use. These adaptations are designed to offset the adverse impacts of climate change (Fig. 1, left) or take better advantage of positive impacts (Fig. 1, right).

It is also worth noting that an analysis of adaptation (Question 3) can also be done under current climate, biophysical, and socio-economic conditions, and this

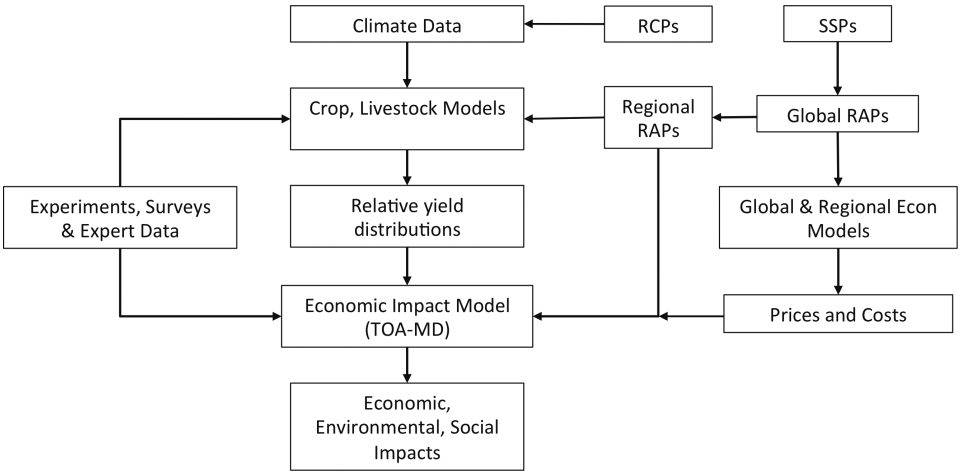


Fig. 2. The AgMIP RIA framework. RCP = representative concentration pathway. SSP = shared socio-economic pathway. RAP = representative agricultural pathway. TOA-MD = Tradeoff Analysis Model for Multi-dimensional Impact Assessment.

would be equivalent to a multi-dimensional impact assessment of a technology as described by Antle (2011).

The AgMIP Regional Integrated Assessment Framework

To implement analysis that could address these three core questions, AgMIP developed an integrated assessment framework for both global and regional analysis (Fig. 2). As in earlier modeling studies, this framework combines climate and biophysical data and models with economic data and models. However, there are several notable features of this framework that represent methodological advances.

A protocol-based approach

One of the major limitations of most previous studies of climate impacts and adaptation is that many different methods for designing scenarios and implementing models are used, and the details of the methods used are not well documented. A major contribution of the AgMIP approach is that it is based on well-defined protocols (as described in detail in the *AgMIP RIA Handbook*, Part 1, Appendix 1 in this volume). These protocols cover all of the components in Fig. 2: the downscaling of climate data (e.g., from the Coupled Model Intercomparison Project, CMIP5); (Taylor *et al.*, 2009), the parameterization and use of crop and livestock simulation models; the creation of pathways and scenarios to project the analysis into the future; and the parameterization and use of economic data and models.

Data and model linkage through new IT tools

A critical component in the implementation of the protocol-based approach is a systematic way to manage both input and output data of the various models. AgMIP has developed a set of new tools to do this, described in Part 1, Chapter 6 in this volume.

Concentration pathways and climate models

The models are implemented for multiple greenhouse-gas concentration pathways (representative concentration pathways, or RCPs; Moss *et al*., 2010), using the more recent CMIP5 data, downscaled to the scale at which the crop and livestock models are implemented (see Part 1, Chapter 3 in this volume for further details). Data from multiple climate models can be used to represent uncertainty in climate projections.

Future development pathways

To characterize future non-climate biophysical conditions and socio-economic conditions, global shared socio-economic pathways (SSPs) are combined with global and regional representative agricultural pathways (RAPs; see Part 1, Chapter 5 in this volume) and data from global economic models to characterize future conditions at the regional and farm level relevant to the analysis of impact and adaptation, as discussed in Chapter 5 in detail. In principle, various SSPs and RAPs can be incorporated into an analysis to represent alternative possible future conditions, and to represent uncertainty about the future.

Impacts of climate change and adaptation on system productivity

Crop and livestock models are simulated on a site-specific basis to characterize the impacts of climate change on the distribution of relative yields (i.e., the yield under future climate conditions relative to the yield under current climate conditions) in the farm population (see Part 1, Chapter 4 in this volume). These relative yield distributions represent the range of yield responses across farms according to site-specific conditions (see below). In principle, multiple crop and livestock models can be used to characterize uncertainty associated with these models. In addition, the models can be used to evaluate how system adaptations could alter the impacts of climate change. For example, changes in planting dates can be modified in crop models, as can fertilizer application rates and irrigation use. Some models also allow alternative crop rotations to be modeled. However, a number of significant limitations to these models must be recognized. Notably, livestock models are limited in the ways that they can represent the effects of climate on livestock productivity; they are aimed at forage supply and direct effects on animals (mortality, productivity,

and fertility), and interactions between crop and livestock systems are not well represented. Moreover, insect pests, diseases, and weeds are not represented in most models, and the effects of climate on these organisms are not well understood or modeled in their own right.

Economic analysis of impact, vulnerability, and adaptation

A fundamental feature of agricultural systems and households is their heterogeneity: they differ in their various biophysical and socio-economic characteristics. A basic hypothesis that underlies the AgMIP approach is that this heterogeneity is a key factor in how systems are impacted by, and how they can adapt to climate change. This heterogeneity is represented in the economic analysis by using relative yield distributions together with farm survey data, RAPs, and data from global economic models. In the studies carried out by the AgMIP regional teams, the economic model called TOA-MD (discussed in more detail below) is used to simulate the average impacts and the distribution of impacts (vulnerability) of farm households to climate change (Core Questions 1 and 2), as well as the potential adoption of systems adapted to climate change and the economic effects of adaptation (Core Question 3). Sensitivity analysis to model parameters can be used to investigate uncertainty associated with the economic model analysis.

The multi-model approach, uncertainty analysis, and the dimensionality problem

Each of the components of the framework allows for scenario and model uncertainty to be represented. However, there are substantial practical limitations to this approach, because the total number of simulations that must be carried out rapidly increases with each dimension of the analysis. In addition, the number of biophysical and economic models that are currently available and appropriate for a given system is limited by data, model scope, and the research team's capabilities. In the case of economic models, the TOA-MD model is the only economic impact assessment model currently available that is generic, documented, and that can be used consistently across multiple systems and locations (Antle *et al.*, 2010, 2011, 2013, 2014).

A Farm-Household System Approach to Regional Integrated Assessment

The AgMIP approach to RIA is built on the concept of the farm household and the farming system that it uses. This approach is fundamental to a meaningful characterization of vulnerability, as well as meaningful analysis of adaptation, particularly for analysis of farm households in the developing world that often rely on a complex mix of crops, livestock, aquaculture, and non-agricultural activities for

their livelihoods. In contrast, most national or regional studies of climate impacts are based on analysis of individual crop or livestock species, or on aggregated economic outcomes such as crop revenue or net returns. These partial, aggregated measures of impact do not provide an accurate representation of vulnerability. Moreover, aggregate analysis cannot represent important aspects of management that are important to climate adaptation.

Implementation of the AgMIP approach begins with the characterization of existing systems, typically by developing "cartoons" or system diagrams (Fig. 3B; also see Part 2, Chapters 1–10 in this volume). The research team uses this characterization of the current systems to identify the key system components, and the corresponding data and models that will be needed to implement the RIA analysis. In addition, this initial characterization helps to develop RAPs by indicating the kinds of variables that need to be included to project the current system and adapted systems into the future (e.g., global and national prices, see Figure 3A).

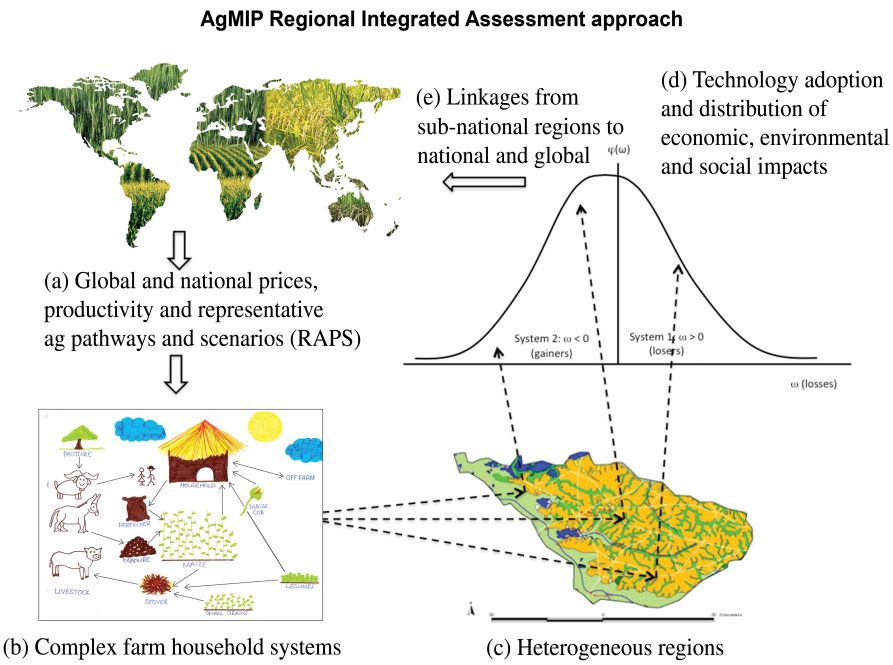


Fig. 3. AgMIP regional integrated assessment approach simulates climate change impact, vulnerability, and adaptation through climate data, biophysical simulation models, and economic models representing a population of heterogeneous farm-household systems. (A) RAPs together with global and national price, productivity, and land-use projections define the biophysical and socio-economic environment in which (B) complex farm-household systems operate in (C) heterogeneous regions. Analysis of technology adoption and (D) impact assessment is implemented in these heterogeneous farm-household populations. This regional analysis may feed back to (E) the country and global scales (farm-household diagram from Part 2, Chapter 5 in this volume).

A key feature of the impact and vulnerability analysis is the representation of biophysical and socio-economic heterogeneity within the farm-household population (Fig. 3C). Acquisition of suitable data to represent all of the main components of the farm-household system is a major challenge in implementing this approach. Typically, farm-household survey data are used to quantify the economic outcomes that are the focus of the impact and vulnerability assessment, as discussed in more detail below and in Part 2, Chapters 1–10 in this volume.

Economic Impact, Vulnerability, and Adaptation Assessment Using the TOA-MD Model

AgMIP uses the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD) to implement the economic analysis component of the regional integrated assessment methodology. The TOA-MD model is a parsimonious, generic model for analysis of technology adoption and impact assessment, and ecosystem services analysis. Antle *et al*. (2010) present a validation of the TOA-MD approach against more complex, spatially explicit models of semi-subsistence agricultural systems. Antle *et al*. (2013) present a validation of the TOA-MD model in an analysis of a major technology adoption and impact assessment study. Further details on the impact assessment aspects of the model are provided in Antle (2011) and Antle *et al*. (2014). The model software and the data used in various studies are available to researchers with documentation and self-guided learning modules at http://tradeoffs.oregonstate.edu. Over 400 researchers globally are now "registered users" of the model, which means that they have completed a basic training course and are using the current version of the model software in a research project.

The chapters in this book by the AgMIP regional teams describe the kinds of farm survey and other data that are used to parameterize the TOA-MD model and its use for climate impact, vulnerability, and adaptation analysis. A complete description of the model and its use can be found in Antle and Valdivia (2014), and at http://tradeoffs.oregonstate.edu.

How does TOA-MD work?

The TOA-MD model simulates technology adoption and impact in a population of heterogeneous farms. Several features of this model are novel as compared to most other economic models that are used for technology adoption and climate impact assessment:

- TOA-MD represents the whole farm production system, which can be composed of (as appropriate) a crop subsystem containing multiple crops, a livestock

subsystem with multiple livestock species, an aquaculture subsystem with multiple species, and the farm household (characterized by the number of family members and the amount of off-farm income).

- TOA-MD is a model of a farm population, not of an individual or "representative" farm. Accordingly, the fundamental parameters of the model are population statistics; means, variances, and correlations of the economic variables in the models and the associated outcome variables of interest. With suitable "matched" biophysical and economic data, these statistical parameters can be estimated for current systems. Using the methods described in the *AgMIP RIA Handbook* (see Part 1, Appendix 1 in this volume), the various elements represented in Fig. 2 can be combined to estimate how the TOA-MD model parameters would change in response to climate change or technological adaptations. These changes in model parameters are the basis for the climate impact, vulnerability, and adaptation analysis.
- TOA-MD simulates impacts that are statistically associated with adoption, using the standard statistical framework for econometric policy evaluation in which economic "agents" — in our context, farms — self-select into "treatment", i.e., choose to adopt or not adopt. The model can be used to estimate the so-called "treatment effects" or the impacts associated with technology adoption. The impacts of climate change estimated by the TOA-MD model are the "treatment effects" of climate change.

As with all models, the TOA-MD model is based on some simplifying assumptions. The key assumptions are:

- In making technology choices, farm decision-makers are assumed to be economically rational. In the version of the model being used by the AgMIP regional teams, technology choice and climate impacts are based on expected economic returns. The simulation model uses data on the spatial variability in observed crop and livestock yields and other variables (production costs, farm size, household size) to represent heterogeneity in the farm population.
- Economic returns in the farm population are assumed to follow a normal (Gaussian) distribution at the lowest level of disaggregation in the analysis (i.e., what are called the "strata" in the TOA-MD model). Thus, an appropriate stratification of the population can play an important role in the analysis. When data are aggregated across strata, the resulting distributions are mixtures of normal distributions and are thus non-normal, as is typically the case in actual data.

Using the TOA-MD model for climate impact assessment

In the TOA-MD model, farmers are presented with a simple binary choice: they can operate with a current or base production System 1, or they can switch to an

alternative System 2. In a technology adoption and impact analysis, the model simulates the proportion of farms that would adopt the new or alternative system, as well as the impacts of the new system by simulating impact indicators defined by the user.

The model is used to assess climate impacts by using a simple analogy to technology adoption. Farmers cannot choose whether to have climate change or not, but if farmers had such a choice, those that would choose to "adopt" climate change are those who would gain from it; farmers that would prefer not to "adopt" climate change are those who would lose from it. An important implication of this model, when used to predict a technology adoption rate, is that the rate is typically between 0% and 100%; it is rare for all farms to adopt a technology because in a heterogeneous population not all farms perceive it to be beneficial. The analogy to climate impact assessment is that there are typically both losers and gainers from climate change. The phenomenon of losers and gainers from climate change can be explained (at least in part) by the heterogeneity in the conditions in which the farms operate, such as soils, water resources, topography, climate, the farm household's socio-economic characteristics, and the broader economic, institutional, and policy setting (see Fig. 3).

In a climate change analysis, it is necessary to distinguish among three basic factors that affect the expected value of a production system: the production methods used, referred to here as the *technology*, the physical environment in which the system is operated, i.e., the *climate*, and the economic and social environment in which the system is operated, i.e., the *socio-economic setting* that we shall refer to as a representative agricultural pathway, or RAP. RAPs are qualitative storylines that can be translated into model parameters such as farm and household size, prices and costs of production, and policy, as discussed in Part1, Chapter 5 in this volume. RAPs represent agricultural development, independent of climate change. Following the three core climate impact assessment questions discussed above, the model can be set up with appropriate combinations of parameters to represent the corresponding technologies, climates, and socio-economic conditions (see Table 1).

Economic foundations of the TOA-MD model

The core of the TOA-MD model is a "threshold" model of technology adoption. A farmer using a production system h (defined as a combination of technology, climate, and RAP) earns returns each period equal to $v_t = v(h)$. Over T time periods, system h provides a discounted net return (V_t) of

$$V(h) = \sum_{t=1}^{T} \delta_t v(h), \tag{1}$$

where δ_t is the relevant time discount factor.

Table 1. Overview of climate, crop model, and economic model components needed in simulation sets required to compare production-system states and answer Core Questions 1, 2, and 3. Note that three crop model cases are defined, and for this table the future period is assumed to be the RCP8.5 mid-century (2040–2069).

Core Questions	Simulation Sets	
1. What is the sensitivity of current agricultural production systems to climate change?	**Current** **Current Climate** **Current Production System** 1980-2009 Climate Crop/Livestock Simulations no Adaptation (#1) TOA without RAP	**Climate Change Sensitivity** **Future Climate** **Current Production System** 2040-2069 Climate Crop/Livestock Simulations, no Adaptation (#2) TOA without RAP
	Economic Simulation #1	

Core Questions	Simulation Sets	
2. What is the impact of climate change on future agricultural production systems?	**Future without Climate Change** **Current Climate** **Current Production System with Trend** 1980-2009 Climate Crop/Livestock Simulations, (no adaptation, with RAP) TOA with RAP 1	**Future with Climate Change** **Future Climate** **Current Production System with Trend** 2040-2069 Climate Crop/Livestock Simulations, (no adaptation, with RAP) TOA with RAP 1
	Economic Simulation #2	

Core Questions	Simulation Sets	
3. What are the benefits of climate change adaptations?	**Future Climate Change without Adaptation** **Future Climate** **Current Production System with Trend** 2040-2069 Climate Crop/Livestock Simulations, no Adaptation (same as #2) TOA with RAP 1	**Future Climate Change with Adaptation** **Future Climate** **Climate-adapted Production System with Trend** 2040-2069 Climate Crop/Livestock Simulations with Adaptations (#3) TOA with RAP 1 and Adaptations
	Economic Simulation #3	

When the production system changes, because of a change in technology or climate or both, expected returns at each site also change. The effect on a farm's returns of changing from one system (call it System 1) to another (call it System 2) is $\omega = V(2) - V(1)$. Thus, if ω is positive it represents the loss, or opportunity cost, associated with switching from System 1 to System 2, and if negative it represents a gain. If we define the density $\phi(\omega)$ as the spatial distribution of gains or losses in the population of farms, the percentage of farms with $\omega < a$ (with a an amount in, e.g., dollars per hectare) is

$$r(a) = 100 \int_{-\infty}^{a} \varphi(\omega) d\omega. \tag{2}$$

In the standard technology adoption analysis, farmers may be able to choose to continue using System 1, which embodies one type of technology (say, the base technology defined above), or to switch to System 2, which embodies a different technology (say, a technology adapted to a different climate). In this case of voluntary technology adoption, note that a farm will switch if $\omega = V(1) - V(2) < a$, which implies that $V(1) < V(2) + a$. Thus $r(a)$ can be interpreted as the proportion of adopters of System 2 that experiences a gain or loss ω from switching, and which are also given a payment (if positive) or made to pay a penalty or tax (if negative) of a dollars per hectare to switch. A farmer with $\omega < 0$ will switch from System 1 to 2 without a positive incentive payment, and $r(0)$ is interpreted as the adoption rate that would occur without an incentive payment or penalty. The model is general and can incorporate a number of different kinds of policy interventions. For example, if a government or other entity wants to encourage additional adoption, a positive incentive can be offered to adopters, in which case the adoption rate is $r(a) > r(0)$ for $a > 0$. Conversely, to discourage adoption, a negative incentive (i.e., a penalty or tax) can be imposed on adopters (say, a tax on the decrease in environmental services associated with the use of System 2).

Climate Impact and Vulnerability Assessment: Answering Core Questions 1 and 2

In a climate impact and vulnerability assessment, ω is interpreted as the loss from climate change, and those farm households that are adversely impacted (i.e., have $\omega > 0$) are defined as vulnerable to climate change. Consider the situation in which farmers are using a particular production system, defined now as System 1. If no adaptation is possible, their only option is to use the same system when the climate changes (call this System 2). In this type of analysis, Equation (2) can be interpreted as showing the proportion of farms with losses less than a, i.e., with $\omega < a$. Thus, $r(0)$ is interpreted as the proportion of farms that are positively impacted, and $1 - r(0)$ is

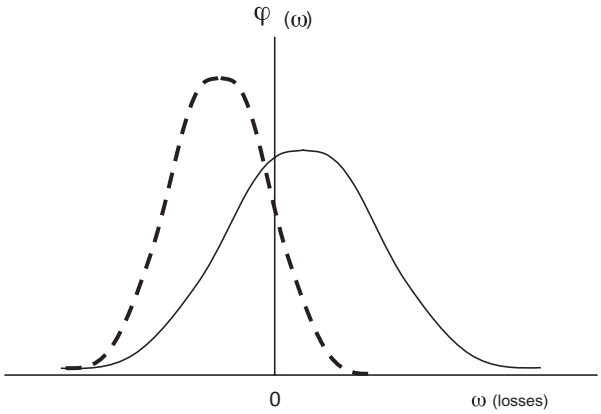


Fig. 4. Vulnerability assessment using the distribution of losses associated with climate change. The area under the distribution on the positive side of zero is the proportion of losers and a measure of vulnerability. Here the solid distribution represents a system for which the average loss is positive and there are more losers than gainers. The dashed distribution represents a system with more gainers than losers. The goal of climate adaptation is to shift the distribution leftward.

interpreted as the proportion of farms that is negatively impacted, and this proportion can be interpreted as a measure of vulnerability to climate change. For Core Question 1, this type of analysis is done under current conditions; for Core Question 2, it is done in combination with RAPs to project the system into the future (Fig. 1 and Table 1).

Figure 4 shows the distribution of losses and illustrates the analysis for two cases. Note that the area under the distribution on the positive side of zero is the proportion of losers and a measure of vulnerability. The solid distribution in Fig. 4 represents a system for which the average change in income is negative and there are more losers than gainers. Note, however, that even in this case there are some gainers, i.e., some individuals in the population for $\omega < 0$. The dashed distribution represents a system that is less vulnerable to climate change, and has more gainers than losers. In this case, even though gainers outnumber losers, there are still some losers with $\omega > 0$. It is also important to note that both the mean and the dispersion of the distribution of gains and losses matters to the measurement of vulnerability. Indeed, the dispersion (i.e., variance) of the distribution of opportunity cost represents the heterogeneity of the impacts of climate change on the population. In the AgMIP RIA methodology, this heterogeneous response to climate change derives from the productivity impacts of climate change incorporated in the model through crop and livestock simulation models (see discussion below), as well as the socio-economic heterogeneity in the farm-household system due to variations in farm size, household size, and non-farm income.

In addition to the proportion of vulnerable farm households, the TOA-MD model can simulate the magnitude of impacts on the adopters (or gainers), the non-adopters (or losers), and the aggregate effect for the entire population. The model calculates impacts on farm net returns, and *per capita* household income, and can also compute income-based poverty rates for the gainers, losers and the overall population. Other outcomes, such as nutritional impacts, can be simulated if suitable data are available (see Antle (2011) and Antle *et al*. (2013) for examples).

Climate Adaptation Analysis: Answering Core Question 3

When farmers are confronted with an environmental change such as climate change, they may choose a different technology that performs better in the new environment, if one is available. Thus, call System 1 the "old" system used with the changed climate, and call System 2 the adapted system used with the new climate, as in Core Question 3 defined above (also see Fig. 1). The TOA-MD model is used in an adaptation analysis to determine the proportion of farms that would adopt this "adapted" system under the changed climate, following the description of an adoption analysis presented above. Using the logic of this model, it follows that with adaptation the proportion of "losers" from climate change would decrease and the proportion of "gainers" would increase. Referring again to Fig. 4, the effect of an adaptation is to shift the distribution of gains and losses leftward, such as the shift from the solid distribution to the dashed distribution. Note that how the adaptation affects both the average loss, as well as the dispersion of losses, will affect the benefits of the adaptation.

Incorporating crop and livestock simulations into the TOA-MD analysis

The analysis of climate impacts, vulnerability, and adaptation depends critically on how the effects of climate change are estimated and incorporated into the economic analysis. The various economic studies in the literature do this in a variety of ways. Some studies directly incorporate climate variables into statistical models that represent average yield, economic returns, land values, or other economic outcomes for some unit of analysis. Most such studies use data averaged over some spatial unit. This type of model can be used to estimate parameters of Systems 1 and 2 in the TOA-MD model, by using them with future climate projections to estimate changes in the economic returns to a production system. However, there are some obvious disadvantages of using these statistical models, most notably the fact that their parameters are based on historical data that embody the historical technological, policy, and social and other conditions in which the farmers represented in the data were operating. Thus, such studies effectively quantify the impacts of projected

future climate on the systems that were observed under past historical conditions. Clearly, when one considers how rapidly technological, social, policy, and other relevant conditions change, the incentives for farmers to adapt to new climate conditions, and the long-term horizons over which climate changes occur, this type of approach is at risk of presenting a substantially biased picture of the impacts of climate change under what are likely to be very different future conditions from past historical experience.

A major goal of the AgMIP methodology is to break out of this "historical" climate impact assessment model. One key element in the analysis is to use process-based crop and livestock simulation models to simulate impacts of climate change on the productivity of the systems in use as well as in adapted systems. As explained in detail in Appendix 1, the *AgMIP Regional Integrated Assessment Handbook* (also see Table 1), the method used for this analysis is to simulate yields under current climate and under future climate, and then to define the *relative yield* as the ratio of the future average yield to the current average yield. These relative yields are simulated for a representative sample of sites in a region, and these data are then used to estimate the *relative yield distribution* in the population. This relative yield distribution is then used to calculate the parameters of the TOA-MD model that shows how climate change may impact the distribution of economic outcomes in the farm population.

Using RAPs and Global Economic Models to Incorporate Future Socio-economic Conditions into the TOA-MD Analysis

As indicated in Figs. 1 and 2 and Table 1, the analysis of Core Questions 2 and 3 are carried out under plausible future conditions defined by RAPs. To project the average level of productivity into the future that would occur with ongoing technological advancements (not associated with climate change or adaptation), the AgMIP methodology utilizes the technology trend projections developed for global economic models (see von Lampe *et al.*, 2014), together with the assessment of technology trends made by research teams in the development of RAPs (see Chapter 5). Likewise, the AgMIP methodology incorporates the price projections from global economic models into the development of regional RAPs.

Conclusions

The AgMIP regional integrated assessment methodology incorporates a number of major advances in the way that climate impact, vulnerability, and adaptation are being modeled. At its core is a protocol approach that should result in impact

assessments being more scientifically credible and thus ultimately having greater value to the various stakeholders. Moreover, the use of the protocol approach should enable closer scrutiny and intercomparison of models and methods so that they can be improved over time. There is also the hope that by creating a truly transdisciplinary, systems-based approach, impact assessments and evaluation of adaptations will be more meaningful to stakeholders. Over time, there is great potential to improve the models and data so that it will be possible to incorporate more important features of current and possible future systems, including multiple crops, inter-crops, livestock, and non-agricultural (e.g., crop insurance) sources of income. It should also be possible with additional research investment to improve the assessment of the key uncertainties in crop, biophysical, and economic dimensions of assessments. The chapters in this volume (Part 2, Chapters 7–10) demonstrating the use of this approach represent a first step towards the eventual full realization of these new methods and their application.

References

Antle, J. M. (2011). Parsimonious multi-dimensional impact assessment, *Am. J. Agric. Econ.*, **93**(5), 1292–1311.

Antle, J. M., Diagana, B., Stoorvogel, J. J., and Valdivia, R. O. (2010). Minimum-data analysis of ecosystem service supply in semi-subsistence agricultural systems: Evidence from Kenya and Senegal, *Aust. J. Agric. Resour. Econ.,* 54601–54617.

Antle, J. M., Jahan, K. M.-E., and Crissman C. C. (2013). *Moving along the impact pathway: Improved methods for estimating technology adoption and multi-dimensional impact — the case of integrated aquaculture-agriculture in Bangladesh*, Final Project report to the Standing Panel on Impact Assessment. Available at: http://tradeoffs.oregonstate.edu. Accessed on 1 August 2014.

Antle, J. M., Stoorvogel, J. J., and Valdivia, R. O. (2014). New parsimonious simulation methods and tools to assess future food and environmental security of farm populations, *Phil. Trans. Roy. Soc. B*, **369**, 20120280.

Antle, J. M. and Valdivia R. O. (2014). Multi-Dimensional Impact Assessment of Agricultural Systems using the TOA-MD Model. Available at: http://tradeoffs.oregonstate.edu. Accessed on 1 August 2014.

Antle, J. M., Valdivia, R. O., Crissman, C. C., Stoorvogel, J. J., and Yanggen, D. (2005). Spatial heterogeneity and adoption of soil conservation investments: Integrated assessment of slow formation terraces in the Andes, *J. Int. Agric. Trade Dev.*, **1**(1), 29–53.

Knowler, D. and Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research, *Food Policy*, 32(1), 25–48.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and 1183 assessment, *Nature*, **463**, 747–756.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2009).*A summary of the CMIP5 experiment design.* Available at: http://cmip-pcmdi.llnl.gov/cmip5/docs/Taylor_CMIP5_design.pdf. Accessed on 1 August 2014.

von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., d'Croz, D. M., Nelson, G. C., Sands, R. D., Schmitz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., and van Meijl, H. (2014). Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison, *Agric. Econ.*, **45**(1), 3–20.

Chapter 3

AgMIP Climate Data and Scenarios for Integrated Assessment

Alexander C. Ruane[1], Jonathan M. Winter[2], Sonali P. McDermid[1,3], and Nicholas I. Hudson[4]

[1]*NASA Goddard Institute for Space Studies, New York, NY, USA*

[2]*Dartmouth College, Hanover, NH, USA*

[3]*Oak Ridge Associated Universities/NASA Postdoctoral Program, Oak Ridge, TN, USA*

[4]*Columbia University Center for Climate Systems Research, New York, NY, USA*

Introduction

Climate change presents a great challenge to the agricultural sector as changes in precipitation, temperature, humidity, and circulation patterns alter the climatic conditions upon which many agricultural systems rely. Projections of future climate conditions are inherently uncertain owing to a lack of clarity on how society will develop, policies that may be implemented to reduce greenhouse-gas (GHG) emissions, and complexities in modeling the atmosphere, ocean, land, cryosphere, and biosphere components of the climate system. Global climate models (GCMs) are based on well-established physics of each climate component that enable the models to project climate responses to changing GHG concentration scenarios (Stocker *et al.*, 2013). The most recent iteration of the Coupled Model Intercomparison Project (CMIP5; Taylor *et al.*, 2012) utilized representative concentration pathways (RCPs) to cover the range of plausible GHG concentrations out past the year 2100, with RCP8.5 representing an extreme scenario and RCP4.5 representing a lower concentrations scenario (Moss *et al.*, 2010).

Figure 1 elucidates the scope of potential climate disruption by presenting median climate change projections from 20 CMIP5 GCMs (Table 1) for RCP8.5 over the 2040–2069 period. Median annual temperature changes (Fig. 1a) range between +1.5°C to +5°C over most land areas, with higher increases over high-latitude

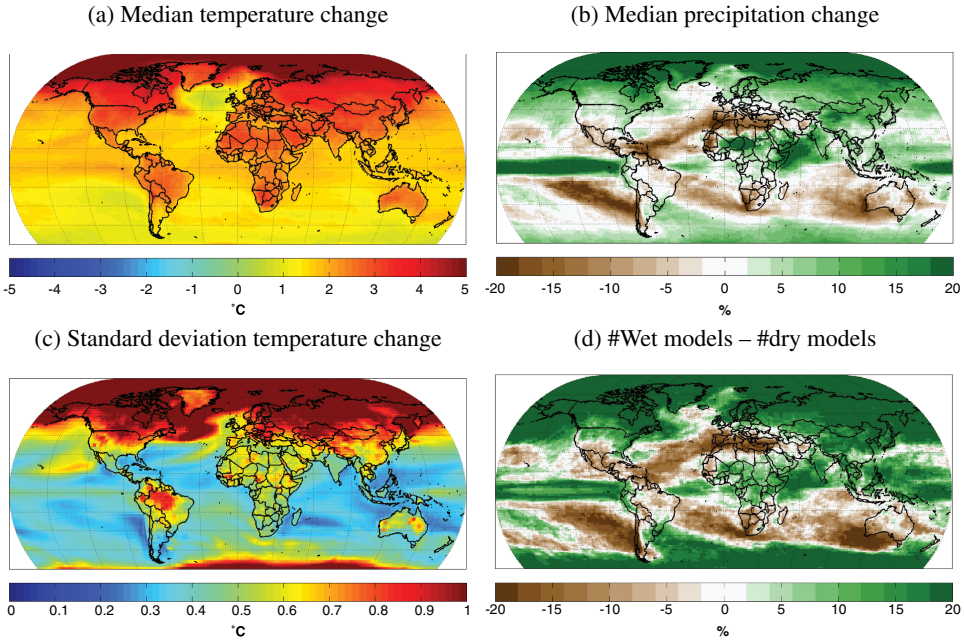


Fig. 1. RCP8.5 2040–2069 median (across 20 CMIP5 GCMs) (a) temperature change (°C) and (b) precipitation change (%) compared to the 1980–2009 historical period, as well as (c) the standard deviation of temperature changes (°C) and (d) the number of models projecting wetter conditions minus the number of models that project drier conditions.

regions and reduced increases over the oceans and coastlines. Mean annual precipitation change projections (Fig. 1b) exceed 20% in some locations and show much larger spatial variability, with wet areas (particularly at high latitudes) generally getting wetter and dry areas becoming more arid. Figure 1c illustrates that temperature change uncertainty across the 20 GCMs generally scales with the median projected temperature change, although local circulation patterns (e.g., the mid-latitude storm tracks) show elevated model uncertainty. Figure 1d presents uncertainty in precipitation change by displaying the difference between the number of GCMs projecting wetter conditions and those projecting drier conditions (i.e., +20 indicates uniform projections of wetter conditions, −20 indicates uniform projections of drier conditions, and 0 means that half of the GCMs projected precipitation changes in each direction). The patterns mimic the median precipitation changes in most regions, although some small precipitation changes (e.g., drying in Mexico or wetter conditions in the eastern US) are revealed as being quite robust.

GCMs were designed to capture the response of the climate system to changes in major climate forcings, such as GHG concentrations; however substantial biases (e.g., in mean climate, climate variability, and extreme events) limit their

Table 1. Summary of 20 CMIP5 GCMs used in AgMIP regional integrated assessments in Sub-Saharan Africa and South Asia (climate sensitivities represent an equilibrium global mean surface-temperature increase resulting from a doubling of pre-industrial CO_2 concentrations; from Table 9.5 of Flato *et al.*, 2013). GCMs in bold are included in the five-member subset of models prioritized for AgMIP investigations.

Model code	GCM	Institution and main reference(s)	Horizontal resolution	2x[CO_2] Eq. climate sens. (°C)
A	ACCESS1-0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia (Bi *et al.*, 2013; Dix *et al.*, 2013)	1.25° × 1.875°	3.8
B	BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration (Wu, 2012; Xin *et al.*, 2013)	∼2.8° × 2.8°	2.8
C	BNU-ESM	College of Global Change and Earth Systems Science, Beijing Normal University (BNU) (Ji *et al.*, 2014)	∼2.8° × 2.8°	4.1
D	CanESM2	Canadian Centre for Climate Modelling & Analysis (Arora *et al.*, 2011; von Salzen *et al.*, 2013)	∼2.8° × 2.8°	3.7
E	**CCSM4**	US National Center for Atmospheric Research (NCAR) (Gent *et al.*, 2011)	∼0.9° × 1.25°	2.9
F	CESM1-BGC	US National Science Foundation (NSF), US Department of Energy (DOE), and the US National Centre for Atmospheric Research (NCAR) (Long *et al.*, 2013; Hurrell *et al.*, 2013)	∼0.9° × 1.25°	n.a.
G	CSIRO-Mk3-6-0	Queensland Climate Change Centre of Excellence and Commonwealth Scientific and Industrial Research Organization (CSIRO) (Rotstayn *et al.*, 2012)	∼1.9° × 1.875°	4.1
H	GFDL-ESM2G	NOAA/Geophysical Fluid Dynamic Laboratory (GFDL) (Generalized Ocean Layer Dynamics with a bulk mixed layer) (Dunne *et al.*, 2012; Dunne *et al.*, 2013)	∼2.0° × 2.5°	2.4

(*Continued*)

Table 1. (*Continued*)

Model code	GCM	Institution and main reference(s)	Horizontal resolution	2x[CO_2] Eq. climate sens. (°C)
I	**GFDL-ESM2M**	NOAA/Geophysical Fluid Dynamic Laboratory (GFDL) (Modular Ocean Model) (Dunne *et al*., 2012; Dunne *et al*., 2013)	~2.0° × 2.5°	2.4
J	HadGEM2-CC	UK Meteorological Office — Hadley Centre (Earth system components — gas phase tropospheric chemistry) (Collins *et al*., 2011; Martin *et al*., 2011)	1.25° × 1.875°	n.a.
K	**HadGEM2-ES**	UK Meteorological Office — Hadley Centre (all Earth system components) (Collins *et al*., 2011; Martin *et al*., 2011)	1.25° × 1.875°	4.6
L	INMCM4.0	Russian Institute for Numerical Mathematics (INM) (Volodin *et al*., 2010)	1.5° × 2°	2.1
M	IPSL-CM5A-LR	Institute Pierre Simon Laplace (IPSL) (low-resolution) (Dufresne *et al*., 2012)	~1.9° × 3.75°	4.1
N	IPSL-CM5A-MR	Institute Pierre Simon Laplace (IPSL) (medium-resolution) (Dufresne *et al*., 2012)	~1.3° × 2.5°	n.a.
O	**MIROC5**	University of Tokyo, Japanese National Institute for Environmental Studies (NIES), and Japan Agency for Marine-Earth Science and Technology (JAMSTEC) (Watanabe *et al*., 2010)	~1.4° × ~1.4°	2.7
P	MIROC-ESM	University of Tokyo, Japanese National Institute for Environmental Studies (NIES), and Japan Agency for Marine-Earth Science and Technology (JAMSTEC) (Watanabe *et al*., 2011)	~2.8° × ~2.8°	4.7
Q	MPI-ESM-LR	Max Planck Institute (MPI) for Meteorology (low resolution) (Giorgetta *et al*., 2014)	~1.9° × 1.875°	3.6

(*Continued*)

Table 1. (*Continued*)

Model code	GCM	Institution and main reference(s)	Horizontal resolution	2x[CO_2] Eq. climate sens. (°C)
R	**MPI-ESM-MR**	Max Planck Institute (MPI) for Meteorology (mixed resolution) (Giorgetta *et al*., 2014)	∼1.9° × 1.875°	n.a.
S	MRI-CGCM3	Japanese Meteorological Research Institute (MRI) (Yukimoto *et al*., 2011; Yukimoto *et al*., 2012)	∼1.1° × 1.125°	2.6
T	NorESM1-M	Norwegian Climate Centre (Iversen *et al*., 2013)	∼1.9° × 2.5°	2.8

n.a = not available.

direct use in climate change impact assessments and applications. Considerable research in the climate community has therefore focused on bias-correction and downscaling of GCM outputs to add some combination of increased horizontal and temporal resolution, better statistics for climate variability and extremes, and interactions between higher spatial- and temporal-scale dynamics and long-term climate changes. Downscaling methods may be dynamical (e.g., utilizing regional climate models, RCMs; see Mearns *et al.*, 2003), statistical (i.e., utilizing historical climate statistics and climate change information; Wilby *et al.*, 2004; Wilks, 2010, 2012), or some combination of the two. For the purposes of agricultural modeling we pay close attention to model biases (which may impede the use of RCMs without bias correction; Glotter *et al.*, 2014) and non-stationarity within the climate system (which may hinder statistical scenario applications). It is important to consider whether the scenario-generation methodology employed captures changes to the variables and time-scales affecting agricultural systems without introducing any compromising biases.

The AgMIP Climate Scenario-Generation Process

Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013) activities span many regions, disciplines, temporal scales, and spatial scales; each potentially requiring unique climate scenario characteristics to understand climate impacts on food security. The AgMIP climate scenario-generation process described below was designed to best suit the needs of the widest possible range of AgMIP activities and AgMIP participants, including those with limited computational resources and low access to long-term, high-quality observational data. AgMIP's integrated assessments require that we solve the

additional challenges of transparent methodologies (enabling reproducible results and protocols that may be followed by many researchers), clarity (such that stakeholders and decision-makers understand what has been done to produce projected results), consistency (allowing results from one region to be more easily compared against another), and practicality (providing a reasonable number of scenarios given additional requirements by the crop, livestock, and economic modelers involved); all the while maintaining our ability to connect to local conditions and gauge uncertain changes.

Exceptions to these criteria are also worth noting, as some agricultural applications may benefit from alternative scenario-generation processes that match the resources, data, and modeling systems utilized. Proprietary tools, models, and methodologies may prove successful, although they are less transparent and reproducible by outside scientists. Applications intended for a purely academic audience may eliminate concerns that stakeholders will not be able to comprehend (and therefore trust) more complex methodologies. Consistency may be less of a limitation for research confined to a specific region, which enables the use of higher-quality observational datasets (e.g., PRISM in the US, Daly *et al.*, 2008; APHRODITE in Asia, Yatagai *et al.*, 2012; E-OBS in Europe, Haylock *et al.*, 2008) or regional climate models (e.g., NARCCAP in North America, Mearns *et al.*, 2009; ENSEMBLES in Europe, van der Linden *et al.*, 2009). In many cases the utility of a given methodology may also be dependent on the availability of high-quality observational data, for example with the bias-correction construction analog approach and the bias-correction spatial disaggregation approach (BCCA and BCSD, respectively; Bureau of Reclamation, 2013). Finally, studies utilizing high-performance computers or those with a primary focus on climate-related uncertainty may be less restricted by additional uncertainties introduced by crop, livestock, and economic models, and therefore may orient a larger portion of their scenarios to gauging climate uncertainty. This would allow for the use of a large ensemble of CMIP5 GCMs and/or associated RCMs, perturbed parameter ensembles (see Part 1, Chapter 9 in this volume), or multiple downscaling or weather generation techniques.

The next sections provide details of the AgMIP climate scenario-generation process conducted for regional integrated assessments, which can be summarized as follows:

- *Utilize a common data format* that facilitates the use of AgMIP information technology tools.
- *Assemble quality-controlled, historical climate data time-series* to calibrate agricultural models and lend confidence to simulations.
- *Estimate climate data time-series at each economic survey location* to capture the ways in which fine-scale climate differences affect household outcomes.

- *Generate future climate scenarios* that connect GCMs and observations with information on uncertainty.

The AgMIP Climate Data Format

AgMIP's interest in providing climate data for consistent agricultural modeling is complicated by diverse requirements from crop, livestock, and economic models. Differences come from the types and units of required variables, temporal resolution, and format of the data files themselves. The latter is especially important in enabling AgMIP's Information Technologies Team to create common utilities across multiple modeling platforms (see Part 1, Chapter 6 in this volume).

The AgMIP climate data format (see Table A1 for an example), which has been used for a number of AgMIP activities dating back to the original wheat pilot (Asseng *et al.*, 2013), describes a single location's weather series and was created to serve as a common basis for conversion into any agricultural model's required format. This format thus aims to include at least the minimal information required to run the majority of crop models, although on occasion these data will need to be converted to calculate additional parameters. Much of the format was adapted from DSSAT's weather file format (Hoogenboom *et al.*, 2012), however important differences are worth highlighting.

AgMIP files are often named according to a convention (Fig. A.1; developed for AgMIP) that conveys additional (although still not comprehensive) information while also meeting DSSAT's limit on eight-character weather-file names (see Appendix 2, Part 1 in this volume for a complete description). The first two letters (#1–2 out of 8) indicate the country by utilizing two-letter country codes developed for internet protocols (http://www.web-l.com/country-codes). The next two characters (#3–4 out of 8) represent the location name within that country. The final four characters represent information about the climate dataset itself. The first of these (#5 out of 8) indicates the time-period and the GHG scenario (SRES for CMIP3 models, Nakicenovic *et al.*, 2000; RCPs for CMIP5 models, Moss *et al.*, 2010), with the current climate (1980–2010) conditions represented as "0". The next character (#6 out of 8) represents the observational or model data source used, for example indicating station observations ("X") or a particular gridded dataset (e.g., AgMERRA = "Q") for historical climate series, a climate model for future climate scenario, or an "S" for imposed values (e.g., from a sensitivity test). The next character (#7 out of 8) indicates additional processing done to this dataset, for example via statistical or dynamical downscaling, adjustment using the WorldClim dataset (Hijmans *et al.*, 2005), or none ("X"). The final character (#8 out of 8) indicates the type of methodology used to create the scenario (described in greater detail

below), for example including none ("X"), a mean-change-only "delta" scenario ("A"), or a scenario including both mean and variability changes ("F"). For sensitivity tests the final two characters (#7–8 out of 8) define the specific sensitivity test created.

The header includes the site name (and four-letter code), latitude, longitude, elevation, and the heights of temperature and wind-speed sensors (estimates of wind-speed profiles within the boundary layer are provided by Allen *et al.*, 1998). The header also includes information about the mean temperature and amplitude (mean-to-peak) of the monthly cycle to facilitate the simulation of seasonal heat conductance through the soil profile. Note that DSSAT requires trough-to-peak amplitude of the seasonal signal, which is twice that of the amplitude provided by the AgMIP format.

AgMIP files contain time-series at daily resolution, preferably covering the 1980–2010 period to include 30 full planting and harvesting cycles even for plants in the ground on December 31, 2009. This period provides at least the minimum number of years to represent a climatology as defined by the World Meteorological Organization (WMO, 1989), however on occasion periods or variables may be marked as missing (fill value = –99). Future scenarios maintain the 1980–2010 dates (even as their naming convention indicates the true time-period) to enable the simulation of many scenarios as separate treatments and also to prevent some crop models from crashing at the omission of a leap day. Dates are provided both in ordinal format (including year and Julian day) and specifically indicating the year, month, and day.

The core variables required for nearly any crop model application include daily maximum and minimum temperatures (T_{max} and T_{min}, in °C), precipitation (mm/day), and solar radiation (MJ/m^2/day). To enable the use of more complex evapotranspiration routines we also include wind speed (m/s), dew-point temperature (°C), vapor pressure (hPa), and the relative humidity (%). These last three variables are all various measures of atmospheric moisture, and are defined to be representative of the time of day of maximum temperature for thermodynamic consistency and to approximate the time of day of maximum evapotranspiration (e.g., when vapor-pressure deficit is greatest and relative humidity is at its diurnal minimum). Though not a perfect estimate owing to the daily time-step, it is important to avoid potential under- or over-estimation of evapotranspiration due to the large diurnal cycle of relative humidity owing to changing temperature and moisture fluxes. Although reference evapotranspiration (ET_0) is used in several crop models (e.g., AquaCrop; Steduto *et al.*, 2009), some other crop models calculate ET_0 internally using the other provided climate variables. As the exact equations vary from model to model, standard AgMIP files leave out ET_0 to avoid dictating a single calculation methodology.

Assembling Quality-Controlled Climate Data Time-Series for the Current Period

Quality assessment of local observations

The ideal agricultural model configuration features a well-maintained, *in situ* meteorological station with comprehensive, consistent, and complete data extending back at least 30 years. In reality, ideal station data-sets are rarely available. Many regions are hampered by a lack of long-term daily weather data, large or spurious gaps in temporal coverage, temperatures and precipitation measured at different locations, absence of observations for secondary variables (e.g., solar radiation, wind speed, humidity), and/or inconsistent observation locations (e.g., a station changing location) or mechanisms (e.g., shifting from subjective sunshine-hour observations to a mechanized pyranometer) over the duration of the dataset.

Although the global network of meteorological stations appears comprehensive (Fig. 2a), these data are not always conducive to agricultural impacts analyses. By comparing major agricultural areas (Fig. 2b) with the 6000+ station datasets compiled by the HadISD station dataset (Dunn *et al.*, 2012), Ruane *et al.* (2014) found 2324 stations in agricultural regions where the 1980–2010 was at least 80% complete for daily temperature measurements and 50% complete for precipitation observations (Fig. 2c). Coverage is particularly poor in developing regions, and total rainfall amounts are often substantially biased due to imprecise and irregular measurements. Climate impact studies are also hampered by difficulties in accessing meteorological observations from national-level agencies, which forces international teams to rely on less-reliable secondary sources of information. Once the best possible dataset is obtained it is important to perform additional quality assessment and quality control.

AgMIP agricultural modeling activities begin with an inventory and simple visualization of available meteorological data, which quickly reveals signatures of many of the above challenges. The desired result is a 1980–2010, AgMIP-formatted climate series. The basic approach is to identify mean biases that may be removed, missing variables that may be calculated from observed variables, dubious data that may be discarded, and resulting gaps that may be filled by using secondary data sources. The procedures used to correct these data are also relevant to the ways in which historical climate data are analyzed, as the mixing of multiple data sources and correction techniques can lead to false trends or extreme statistics. Acknowledging that quality assessment and quality control of any given station may require unique approaches, AgMIP activities recommend the following guidelines:

- Identify spurious data by calculating daily standard deviations within each month and flagging any data point exceeding three standard deviations from the long-term

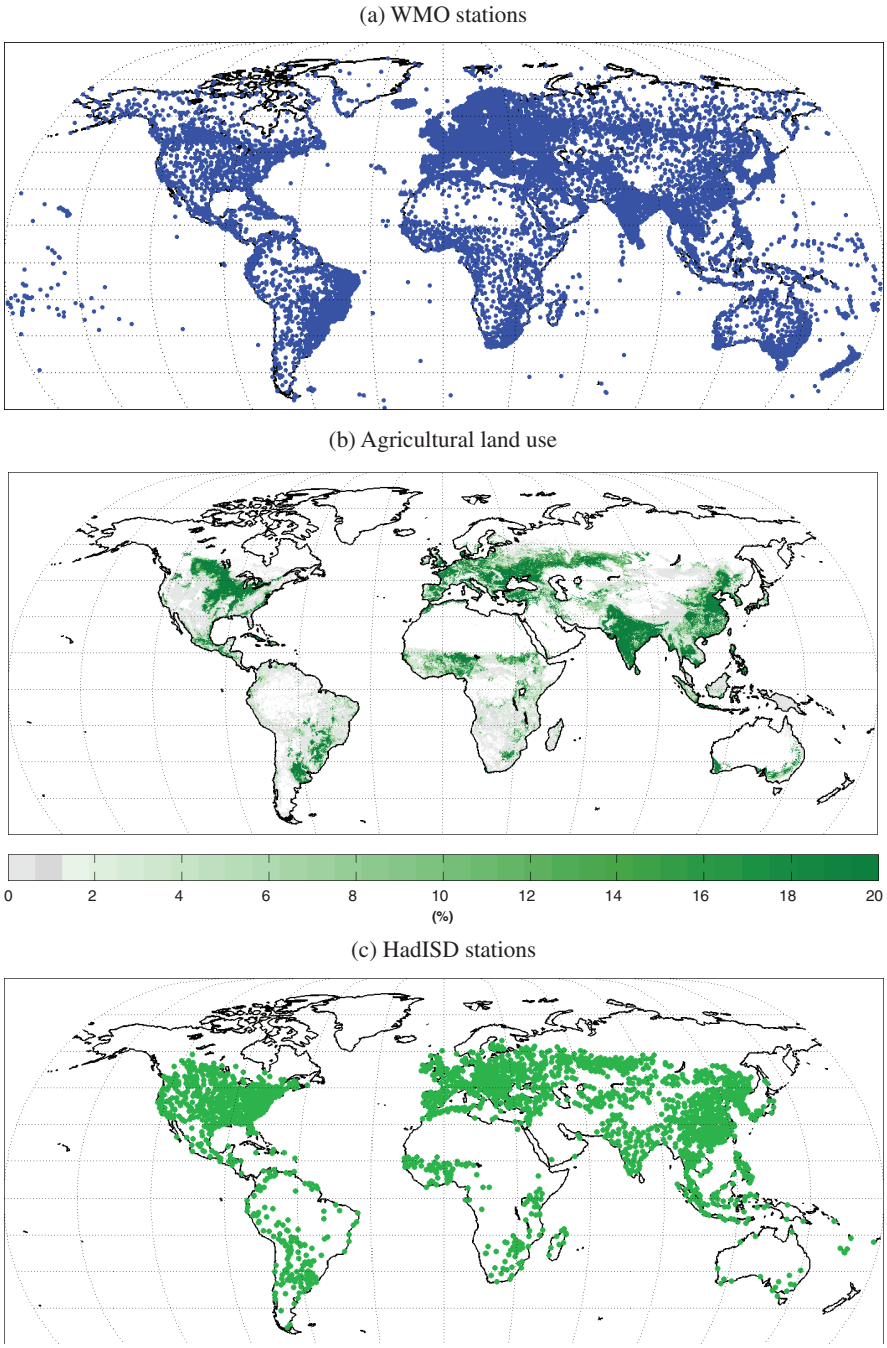


Fig. 2. Coverage of meteorological stations in agricultural regions. (a) Network of all WMO stations; (b) percentage of land used for agricultural purposes (major crops from Monfreda *et al.*, 2008; note that some regions have agricultural land use over more than 25% of land areas); (c) subset of HadISD stations with >80% of daily temperature values and >50% daily rainfall values over the 1980–2010 period that also fall on agricultural lands.

average. These points should not be tossed by rule, but should instead be examined for physical consistency (e.g., do minimum and maximum temperatures both show a spike?), persistence (e.g., does an extreme event show reasonable temporal evolution?), arbitrary values (e.g., many events with exactly 120 mm of rain), spatial coherence (e.g., nearby stations show similar extremes), historical account (e.g., newspaper record of extreme event), or independent dataset (e.g., the spike also occurs in retrospective analyses).

- If there is evidence that a bias has been introduced by a station moving location, remove that bias by using monthly averages that compare before and after the move occurred.
- Avoid using local solar radiation measurements, which are often poorly maintained. Instead, such measurements are easily replaced by using the NASA/GEWEX solar radiation budget dataset (SRB; see White *et al.* (2011), for a comparison of crop model results) or the AgMERRA results described below.
- Calculate moisture values to be consistent at the time of day during which the maximum temperature occurs. If moisture information is provided for a different time of day, use the corresponding temperature to convert to vapor pressure (T_{dew} and vapor pressure do not fluctuate during the day as widely as relative humidity). For example, if average relative humidity is measured, convert this value to vapor pressures by using the average of T_{max} and T_{min}, then re-calculate relative humidity by using T_{max}.
- Use the value –99 to denote missing values.

The AgMERRA dataset

Once data gaps have been identified in a station dataset we turn to a secondary data source to fill in these gaps. Ruane *et al.* (2014) describe the creation of the AgMERRA and AgCFSR climate datasets as a globally consistent product with the temporal, spatial, and variable coverage required for agricultural modeling. We provide a brief description of AgMERRA here, as it is used for gap-filling and historical climate series estimation in AgMIP activities.

AgMERRA is a post-processing of the NASA Modern Era Retrospective-Analysis for Research and Applications (MERRA; Rienecker *et al.*, 2011) suitable for agricultural modeling, featuring considerable bias adjustment and integration of additional information. AgMERRA utilizes the MERRA-Land land-surface reanalysis of MERRA outputs conducted by Reichle *et al.* (2011), allowing additional assimilation of coarse five-day precipitation observations from the Global Precipitation Climatology Project (GPCP; Huffman*et al.*, 2009). Monthly precipitation totals are corrected to match the average of three global gridded gauge datasets (CRU, Harris *et al.*, 2013; WM, Willmott and Matsuura, 1995; GPCC, Schneider

et al., 2011), and then $\frac{1}{4}^\circ \times \frac{1}{4}^\circ$ spatial patterns of precipitation are imposed from three high-resolution satellite products (Huffmann *et al.*, 2007; Hsu *et al.*. 1997; Joyce *et al.*, 2004). Temperature bias is removed in a similar manner by using two of the global gridded observational datasets (Harris *et al.*, 2013; Willmott and Matsuura, 1995) and a correction for the diurnal temperature range. Solar radiation is directly imposed from the NASA/GEWEX SRB (Stackhouse *et al.*, 2011), with early and late years formed by adjusting MERRA in the absence of SRB data. Wind speeds and moisture variables at the time of day of $T_{\max}$ are taken directly from MERRA.

AgMERRA is therefore well suited for agricultural modeling, featuring all of the variables required to compute daily AgMIP-formatted climate series from 1980–2010 for nearly all land-points (exceptions are those areas that are permanently glaciated and some small islands). AgMERRA has a nominal resolution of $\frac{1}{4}^\circ \times \frac{1}{4}^\circ$, however some variables are effectively of a coarser resolution owing to bias-correction methods (solar radiation comes from a $1^\circ \times 1^\circ$ dataset, and mean temperature comes from a $\frac{1}{2}^\circ \times \frac{1}{2}^\circ$ dataset).

Figure 3 presents a summary of AgMERRA validation analyses across the 2324 meteorological observation sites in agricultural regions identified in Fig. 2c. In general, maximum temperatures are biased slightly too warm while T_{min} is biased slightly too cool (which implies an inflated diurnal cycle), although these biases are less than 1°C for the vast majority of stations (Fig. 3a). These biases largely counteract each other when averaged together, falling within $\pm\frac{1}{4}^\circ$C of observations for more than one third of the examined stations. Mean precipitation also falls within $\pm 10\%$ of the global gridded precipitation observations for most stations (Fig. 3b). AgMERRA daily temperature correlations usually exceed 0.8 and approach 0.98, while daily precipitation correlations, which one would expect to be lower owing to rainfall's stochastic nature, most often lie near 0.6 and reach above 0.8.

Ruane *et al.* (2014) compared ten climate-forcing datasets and reanalyses and found that AgMERRA performed substantially better at capturing daily precipitation patterns and the sub-seasonal distribution of precipitation events (owing largely to the use of the MERRA-Land dataset). AgMERRA's performance was also comparable or better than other datasets for mean precipitation and other variables, which lends confidence to its use in AgMIP activities when robust local observations are not available. It is important to note that the blending of model and observational datasets within AgMERRA (and any other climate-forcing dataset) makes it less suitable for trend analysis and water- or energy-budget studies.

Gap-filling with bias-corrected AgMERRA dataset

Figure 4 presents a demonstration of recommended methodologies for gap-filling using the National Climatic Data Center's Global Summary of the Day (GSOD)

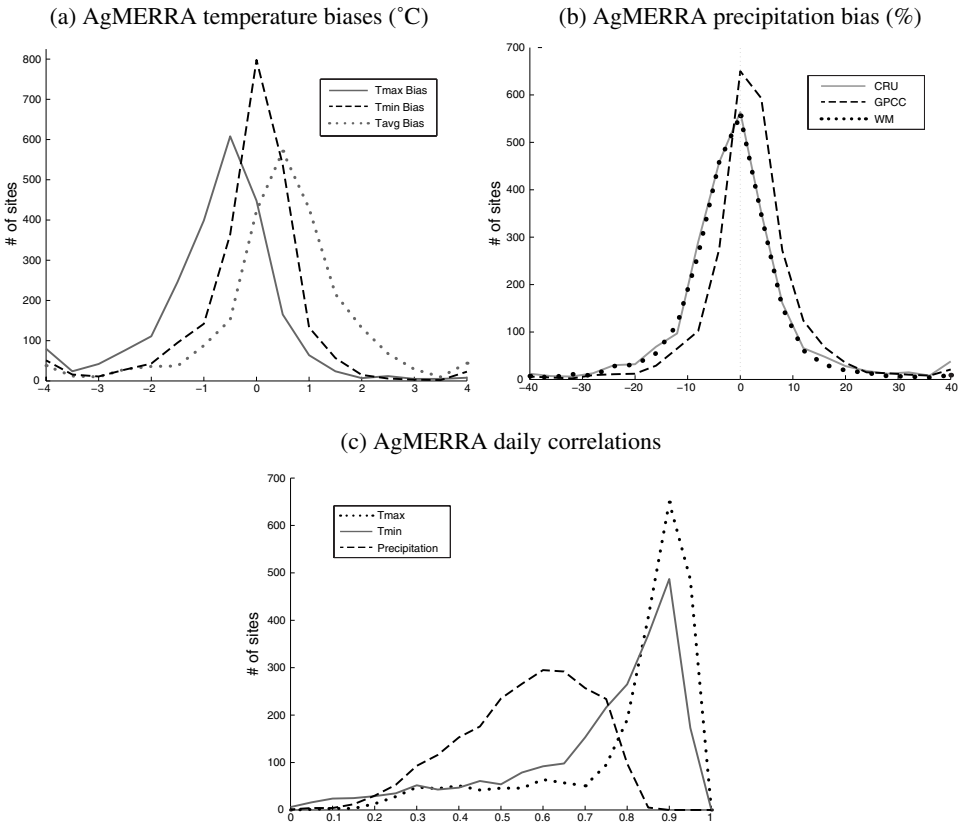


Fig. 3. Comparison of AgMERRA and at the locations corresponding to selected HadISD network of long-term meteorological sites in agricultural regions. (a) Mean annual temperature biases versus HadISD; (b) mean annual precipitation biases of three gridded gauge products against AgMERRA; and (c) daily correlations against HadISD.

for Niamey, Niger. Fig. 4a compares this *in situ* maximum temperature dataset (with an imposed gap covering 1993–1994) against the AgMERRA time-series corresponding to the same location (2.13°E, 13.48°N), revealing a slight warm bias in AgMERRA but good overall correspondence on seasonal and subseasonal variability. We calculate average monthly biases between the datasets using all days (N) within a given month (m) where GSOD data exist ($d\exists GSOD$); using subtracted differences for $T_{\max}$ and $T_{\min}$ and fractional differences for precipitation (and other AgMIP variables):

$$Bias_{T_{\max,\mathrm{m}}} = \frac{1}{N_{d\exists GSOD,\mathrm{m}}} \sum_{d\exists\, GSOD,\mathrm{m}} \left(T\max_{GSOD} - T\max_{\mathrm{AgMERRA}}\right) \qquad (1)$$

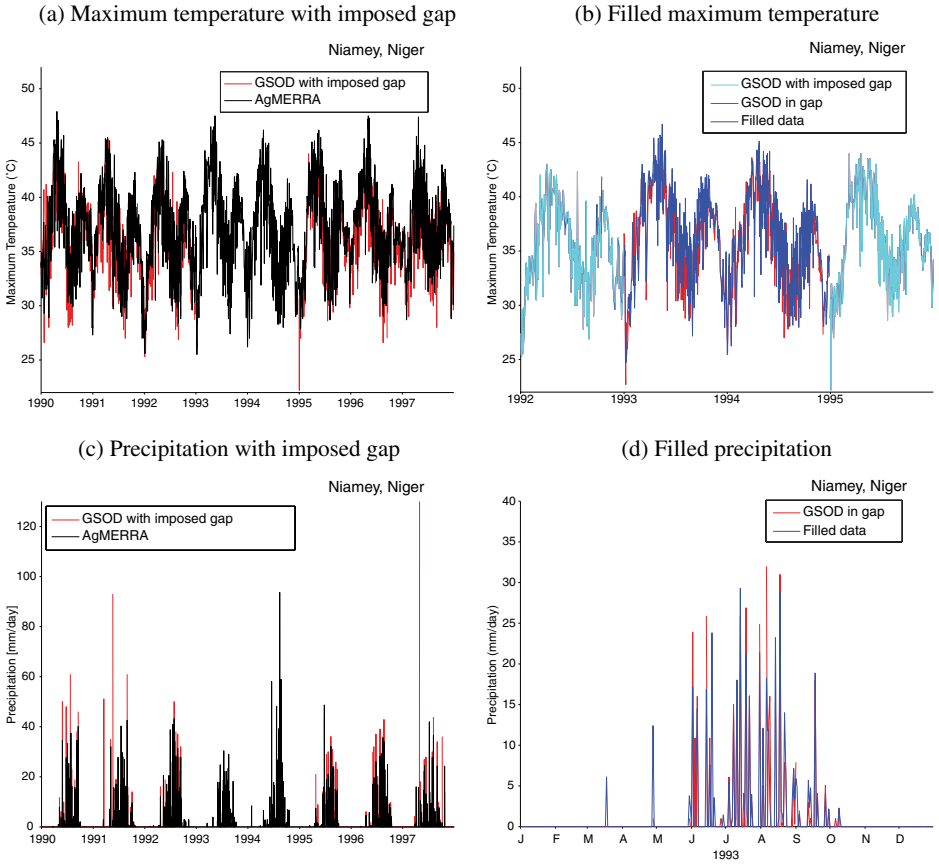


Fig. 4. Demonstration of gap-filling for Niamey, Niger. (a) Maximum temperature series from AgMERRA and the NCDC GSOD with imposed gap from 1993–1994 and several additional missing days; (b) the filled-in temperature values for 1993–1995 and the original data that were removed; (c) precipitation time-series from AgMERRA and the NCDC GSOD with imposed gap covering 1993–1994; (d) the filled-in precipitation values for 1993 and the original data that were removed.

$$Bias_{T_{\min,\mathrm{m}}} = \frac{1}{N_{d\exists GSOD,\mathrm{m}}} \sum_{d\exists\, GSOD,\mathrm{m}} \left(T\min_{GSOD} - T\min_{\mathrm{AgMERRA}}\right) \tag{2}$$

$$Bias_{P,\mathrm{m}} = \frac{1}{N_{d\exists GSOD,\mathrm{m}}} \sum_{d\exists\, GSOD,\mathrm{m}} (P_{GSOD}) / \sum_{d\exists GSOD,\mathrm{m}} \left(P_{\mathrm{AgMERRA}}\right) \tag{3}$$

Data gaps fewer than four days long were filled using simple linear interpolation from the observed points on either side of the gap (with short precipitation gaps set as dry), and then longer gaps were filled by adjusting the AgMERRA dataset with the corresponding monthly bias correction (from Equations 1–3; adding temperature biases and multiplying other variable biases). The result is shown in Fig. 4b, revealing

the final GSOD dataset, the portion that was filled in, and the actual dataset that was removed to impose the gap.

A demonstration of these procedures is also shown for Niamey precipitation (Figs. 4c, 4d). The exact correspondence of AgMERRA and GSOD precipitation is weaker than was evident in T_{max}, as would be expected for the more stochastic and spatially complex rainfall. Zooming in on 1993, the gap-filling procedure demonstrates a reasonable representation of the overall patterns and averages of rainfall, even matching many specific events that were well captured by AgMERRA.

Estimating Farm-Based Climate Data Time-Series

The sparse *in situ* spatial network (recall Fig. 2a) often leads to a paucity of suitable stations for historical climate estimation. Stations more than 100 km away are susceptible to differences in mean conditions as well as in the day-to-day sequence of passing weather events, so on occasion the AgMERRA dataset may be preferable as a basis for historical conditions. As AgMERRA's internal biases are likely to be spatially coherent, in these situations it is still advisable to calculate mean monthly biases (Equations 1–3) for the nearest weather station (by using corresponding AgMERRA data) and apply those corrections to the AgMERRA series for the modeling site.

Even when a nearby station is identified, in many cases complex topography or coastlines can lead to substantial biases in comparison to true field conditions. These fine-scale climatological patterns may also be an important element in reproducing differences between various farms surveyed as part of AgMIP regional integrated assessments, however fine differences in AgMERRA are resolvable only down to ~50 km spatial scales.

For finer-scale information we utilize the 5 km version of the WorldClim dataset (Hijmans *et al.*, 2005). Note that we make no direct comparison between WorldClim and observed station data, but seek only to utilize WorldClim as an estimate of spatial differences. The WorldClim dataset provides a mean climatology for each month (e.g., one map for baseline April temperatures) using a large network of *in situ* stations and interpolation algorithms based on topographic adjustments (similar to PRISM in the US; Daly *et al.*, 2008). These input stations include the WMO's network (Fig. 2a) and therefore have the same challenges in terms of lower station density in developing regions and data quality issues at many locations.

In comparison to AgMERRA, WorldClim's fine-scale geographic patterns on a sub-100 km spatial scale can estimate cooler climates for farms located near major bodies of water, increased precipitation on some higher-elevation households, and

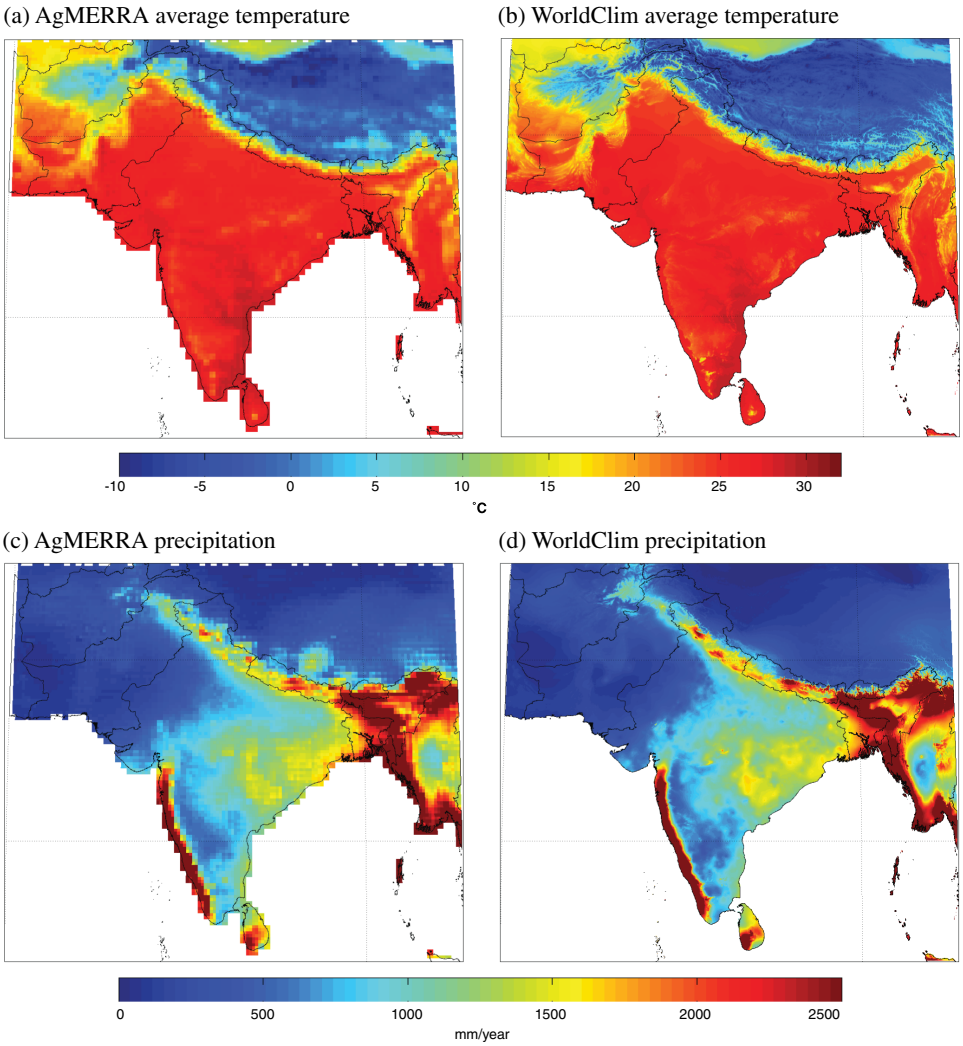


Fig. 5. Comparison of AgMERRA and WorldClim for mean annual (a, b) temperature (°C) and (c, d) precipitation (mm/year) over South Asia.

other mesoscale features (Fig. 5). Equations 1–3 may therefore be applied again to determine mean spatial differences between the quality-controlled historical climate location and the location of an individual farm where modeling will occur, allowing mean climate differences to factor into regional distributions of yield even when the day-to-day variability is assumed to be consistent within a small region. For example, if a farm is 0.6°C warmer in August than the site that corresponds to the weather station in WorldClim, August days in that farm's climate series can be adjusted to be 0.6°C warmer than the weather station (regardless of

mean differences between the weather station and WorldClim itself). An R programming script to perform these spatial adjustments is described in Hudson and Ruane (see Appendix 2, Part 1 in this volume).

Generation of Future Climate Scenarios

Two types of climate scenarios were produced for the AgMIP integrated assessments in Sub-Saharan Africa and South Asia (see Part 2, Chapters 1–10 in this volume). The basis for each future climate scenario was the quality-controlled historical climate, with climate information at each farm location as described above. In this approach, the future climate scenarios are based on a climate system with spatial and temporal patterns recognizable to stakeholders and decision-makers within the study regions. To make future climate change predictions we adjust these historical series according to specific parameters drawn from future climate change projections.

Climate scenarios for integrated assessments were drawn from 20 GCMs (Table 1) selected when the AgMIP regional integrated assessments initiated (April, 2012) as those with available daily outputs for both RCP8.5 and RCP4.5 extending out to 2100 in the online archive of the Program for Climate Model Diagnostics and Intercomparison (PCMDI). Hudson and Ruane (see Appendix 2, Part 1 in this volume) present a series of R scripts that enable researchers to generate the climate scenarios described below for their own locations.

Selecting a subset of future scenarios for regional integrated assessment

As integrated assessments also include various adaptation packages (see Part 1, Chapter 4 in this volume) and representative adaptation pathways (RAPs; see Part 1, Chapter 5 in this volume), the full scope of GCMs, time-periods, scenarios, and scenario types were not practical. Future climate analysis therefore focused on the mid-century period (2040–2069) under the RCP8.5 (more extreme) GHG scenario. We chose a subset of five GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR; in bold text in Table 1) for complete analysis according to the following criteria:[1]

- Spatial resolution (higher resolution was desirable).
- Prominence in peer-reviewed studies (a more robust history of validation was preferred).

[1]Note that climate sensitivity was not an explicit criterion in selecting the GCM subset, although the resulting five-GCM subset (2.4 to 4.6°C) reasonably spans GCM sensitivities (2.1 to 4.7°C) (see Table 1).

- Participation in past CMIP activities (modeling groups with long records of participation in the major climate model projections and intercomparisons were preferred.
- Performance in monsoon regions (see discussion below).

Monsoon performance was considered especially important considering AgMIP's study regions across Asia and Sub-Saharan Africa. In addition to the prominent West African Monsoon, the South Asian and East African climates are sensitive to fluctuations in the overlying atmospheric circulation and the South Asian Summer Monsoon (SASM), particularly with respect to interannual climate variability, seasonal rainfall totals, and rainfall distribution. GCMs can elucidate the mechanisms by which the SASM (and its atmospheric teleconnections) can impact regional rainfall on seasonal, interannual, and decadal times-cales. To do this accurately, GCMs must be able to reproduce certain key regional climatic features accurately, including: the major rain belts across the Indo-Gangetic plains and the monsoon trough; the rainfall maximum along the southwestern Indian coast; the respective national total rainfall amounts during the SASM months (June–September); the interannual variability in this rainfall; and the spatial distribution of this rainfall (Kripalani *et al.*, 2007; Sabade *et al.*, 2010). A review of numerous studies examining GCM resolution of the features related to the Indian Ocean monsoon (e.g., Delworth *et al.*, 2012; Deser *et al.*, 2012; Kripalani *et al.*, 2007; Irving *et al.*, 2011; Meehl *et al.*, 2012; Sabade *et al.*, 2010) helped ensure that the GCM subset was appropriate for application in monsoon-affected AgMIP study areas.

The same five GCMs were examined in each AgMIP study area in order to facilitate comparisons across regions. To determine the implications of selecting a five-GCM subset to represent the wider array of GCMs (there are now more than 50 CMIP5 GCMs in PCMDI), AgMIP integrated assessment teams compared basic climate information from the subset to the wider ensemble. Figure 6 compares this five-GCM subset with the wider 20-GCM ensemble over three time-slices in the 21st century at Shizukuishi, Japan (39.70°N, 140.97°E; a site used in the AgMIP Rice Pilot; Li *et al.*, 2014), showing a reasonable spread within the subset but also revealing that more extreme projections may not be captured.

Mean change scenarios

The first climate change scenarios examined in AgMIP research activities has been the mean change scenarios (also known as "delta" scenarios; Wilby *et al.*, 2004) that have been the leading scenario-generation approach for crop modeling studies of climate impacts (White *et al.*, 2011). These scenarios simply impose mean

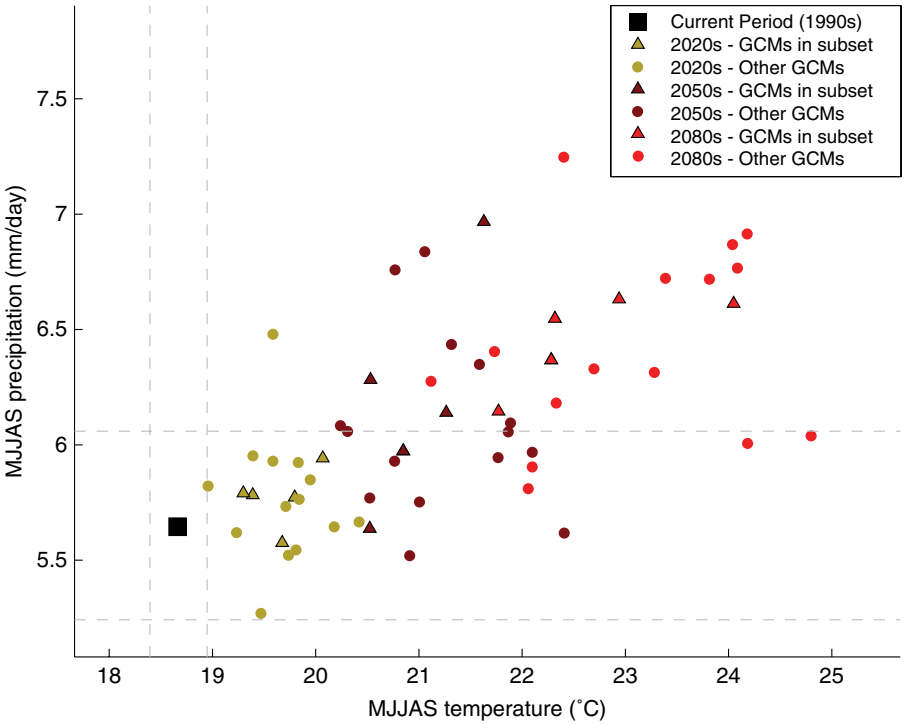


Fig. 6. Spread of GCM projections for growing season temperature and precipitation changes from the baseline conditions at Shizukuishi, Japan, with RCP8.5 scenarios presented for the near-term (2010–2039), mid-century (2040–2069), and end-of-century (2070–2099) time-slices from the 20 CMIP5 GCMs listed in Table 1. Triangles represent the subset of five GCMs in focus for the regional integrated assessments in South Asia and Sub-Saharan Africa, while dots represent the other GCMs in the same scenario. Changes that exceed the dashed lines are significantly different from historical conditions at the 95% confidence level.

changes in T_{max}, T_{min}, and precipitation on the quality-controlled historical time-series in a manner similar to the bias correction described above (see Appendix 2, Part 1 in this volume for R scripts generating mean-change-only scenarios). In this case, instead of correcting for a bias we adjust the historical time-series according to changes in climate indicated by comparing a GCM's projections for a future time-slice (e.g., 2040–2069) against the same GCM's historical period (1980–2009) utilizing Equations 1–3. Mean monthly temperature changes are added, and mean monthly precipitation changes are imposed via a multiplicative factor. Solar radiation, wind, and relative humidity are not altered; however dewpoint temperature and vapor pressure are adjusted to maintain thermodynamic coherence with the daily relative humidity and maximum temperature. Figures 7a, 7b visualize the historical climate series (blue) and an example delta scenario (red) created for Chinoli, Bolivia (19.63°S, 65.37°W; a site used in the AgMIP Potato Pilot). Key properties of the

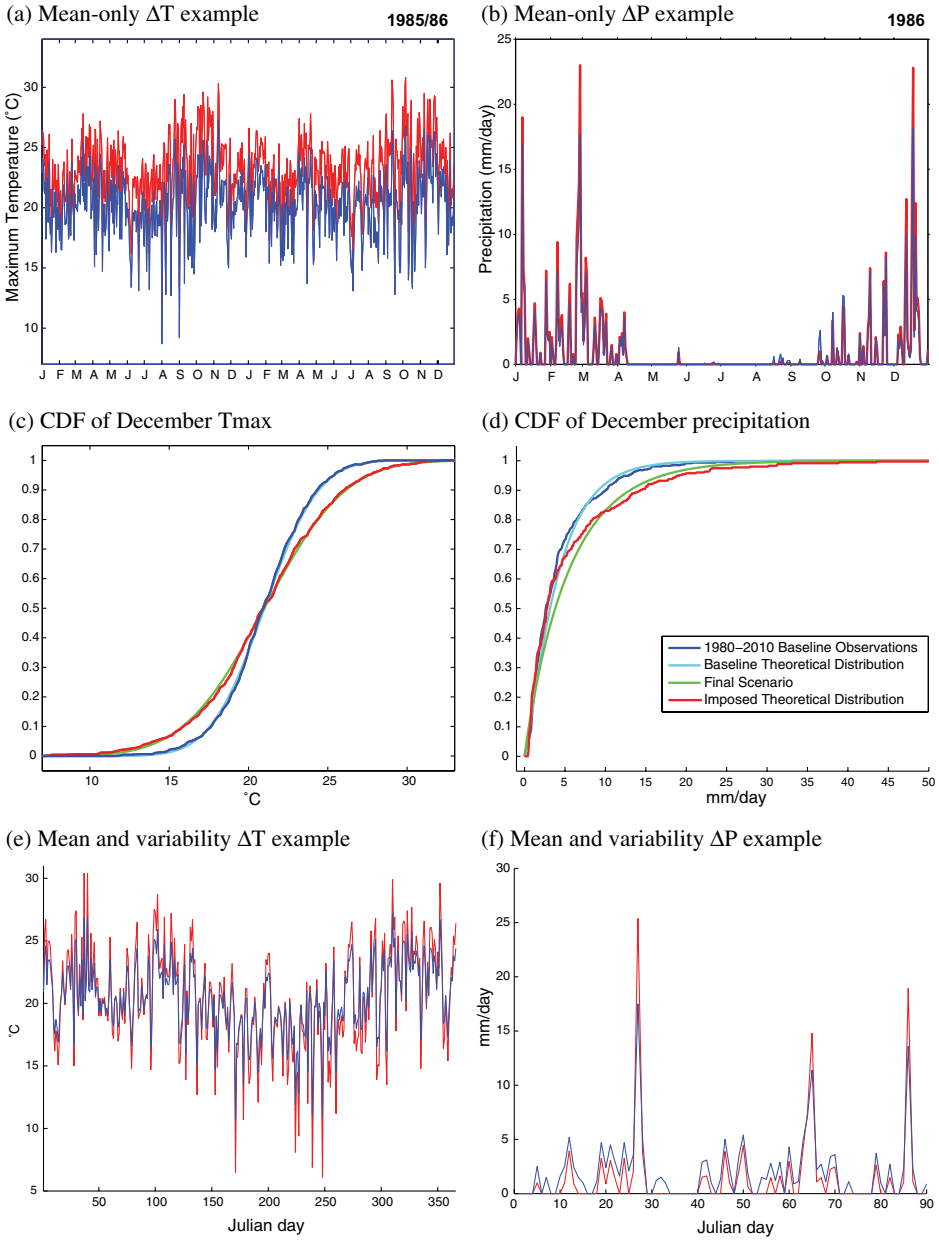


Fig. 7. Example of climate scenarios prepared for crop and livestock model assessment for Chinoli, Bolivia. Baseline and mean-change-only delta scenarios for (a) maximum temperature and (b) precipitation; comparison of actual and theoretical cumulative distribution functions for baseline and future scenarios produced with mean and variability changes consisting of a 50% increase in the standard deviation of (c) maximum temperature, and a 25% reduction in the number of wet days and 25% reduction in the shape parameter of the gamma distribution for (d) precipitation; resulting daily time-series for (e) maximum temperature and (f) precipitation.

delta scenario methodology are apparent, including:

- Maintenance of observed climate variability (sub-seasonal and interannual).
- Coherence of precipitation events and coincidental temperature anomalies.
- Potential adjustment of seasonal cycle (each month may have different change factors).
- Changes in rainfall intensity, but no adjustment to rainfall frequency.
- Scenario contains the same number of years and days as the historical time-series.
- Removes GCM mean biases that are present in both historical and future periods, taking only the projected climate changes into account.

Each of these properties has its strengths and weaknesses. For example, directly using the historical climate variability maintains nearly all modes of variability (which other statistical scenario approaches have a tendency to truncate), however this approach does not allow climate change to interact with climate variability (which is highly likely to occur but difficult to project). The strengths of this approach are that it utilizes well-vetted portions of GCM projections (mean changes in temperature and precipitation) without being overly dependent on other variables and time-scales, and also that it is well established in the literature so that its shortcomings are well known in the scientific community and by many stakeholders.

Figures 6 and 8 present two ways of visualizing delta scenarios while considering uncertainties (using Shizukuishi, Japan, as an example). The former presents the growing season climate changes for the 20-GCM ensemble, allowing uncertainty to be quickly gauged for temperature, precipitation, and time-period evolution. To gauge the significance of climate changes, we employ the Z-test to determine the probability that natural variability (Q_{std}; calculated as the standard deviation of a quantity's growing season averages) could randomly create an N-year period with the same mean change in that quantity imposed by the delta scenario methodology:

$$Z = abs(\mu_2 - \mu_1) * \frac{\sqrt{N}}{Q_{\text{std}}} \tag{4}$$

As AgMIP time-slices are often 30 growing seasons long and $Z = 1.96$ is the threshold for significance at the 95th percentile level, we can re-organize Equation 4 to find that the threshold for significance is ~36% of the Q_{std}:

$$\Delta Q_{\text{threshold}} = \frac{1.96}{\sqrt{30}} * Q_{\text{std}} = 0.3578 * Q_{\text{std}} \tag{5}$$

A similar analysis indicates that mean changes exceeding 47% of Q_{std} are required to surpass 99th percentile significance. Including the 95th percentile thresholds as dashed lines in Fig. 6 makes it clear that projected temperature changes are robust,

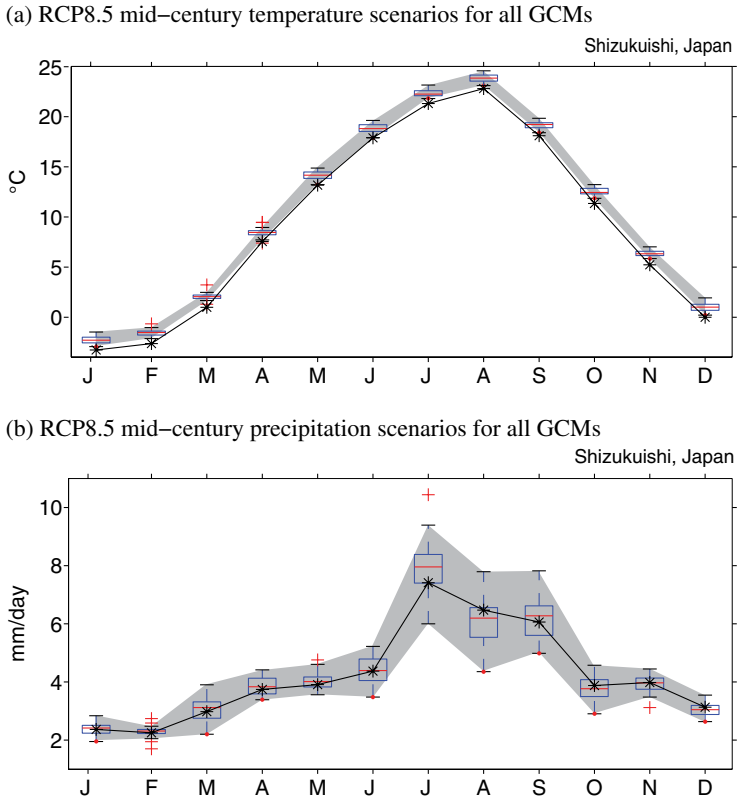


Fig. 8. Comparison of baseline and future climate scenarios for Shizukuishi, Japan. 1980–2010 mean baseline conditions are represented as the black line and asterisks, and 20 GCM scenarios from the RCP8.5 mid-century (2040–2069) time-slice are shown as a box-and-whisker diagram by month and for annual and seasonal averages for (a) mean temperature and (b) mean precipitation rate.

while many of the models project precipitation changes will be hard to distinguish from historical variability until at least the middle of the 21st century.

Figure 8 presents the historical mean temperature and precipitation for each month as well as seasonal and annual means (black stars and lines), then places a box-and-whisker diagram on top to show the spread of delta scenarios throughout the year. This presentation illustrates a robust temperature increase for all seasons in Shizukuishi. Precipitation changes are less certain but do show seasonal patterns that may be important for agricultural planning and adaptation (e.g., median precipitation changes are positive for the beginning of the monsoon season in June but negative in the middle of the monsoon season in July). This visualization also better communicates the implications of seasonal precipitation change factors by applying them to observed totals, revealing for example how months with low precipitation totals are not strongly affected by even large precipitation change factors.

Mean and variability change scenarios

AgMIP regional integrated assessment researchers in Sub-Saharan Africa and South Asia also created more complex future climate scenarios that allowed for changes in both mean climate and its variability (see see Appendix 2, Part 1 in this volume for R scripts that generate mean and variability scenarios). The procedure is similar to the delta method with GCM-projected climate changes imposed on historical climate series. In this case, however, in addition to changes to monthly mean T_{max}, T_{min}, and precipitation, changes may also be imposed on the standard deviation of daily T_{max} and T_{min} as well as upon the number of rainy days and the shape of the rainfall distribution. Rather than changing only the mean conditions, mean-and-variability scenarios adjust the monthly distribution of climate variables; assuming a Gaussian fit (defined by mean and standard deviation) for T_{max} and T_{min} and a gamma distribution (defined by mean precipitation, the number of rain events, and a shape parameter) for rain events when they do occur (Wilks, 2011). In this way we stretch the historical time-series to mimic future projections where mean and variability changes have occurred.

We use the Chinoli, Bolivia location to illustrate the mean and variability approach (Figs. 7c–f) assuming no changes in mean but a 50% increase in the standard deviations of temperatures, a 25% reduction in the number of wet days, and a 25% reduction in the shape parameter for precipitation. The 1980–2010 period gives us between 875 and 961 individual days for any given month over the 31-year time-span from which to form the historical distributions. It is unsurprising that the actual distributions differ from the theoretical fit (constructed from the calculated distributional parameters of the baseline climate) even with this many days, as is clear in the subtle differences between the actual and theoretical distributions in Fig. 7c (T_{max}) and Fig. 7d (precipitation). The steps occasionally evident in the dark-blue lines reflect discrete measurement increments and rounding that often occurs in meteorological observations, but the larger deviations are signatures of skew and local climate behaviors that likely reflect thermodynamic or circulation patterns that tend to favor some events more than others.

The CMIP5 global climate modeling teams submitted a considerable number of daily climate outputs that can inform the calculation of changes in variability parameters. Upon calculating monthly changes in the mean and standard deviation of T_{max}, for example, a target theoretical distribution (Fig. 7c) can be calculated. For precipitation, the number of rainy days must first be adjusted (eliminating the driest days to reduce the total or adding precipitation on the cloudiest days to add to the total; see Ruane *et al.*, 2014), but then the mean and shape parameter allow its own theoretical distribution (Fig. 7d) to be calculated. To generate the new scenario, each event from the historical period is shifted according to the difference between the

historical theoretical distribution and the future theoretical distribution, resulting in the new scenario. Temperature changes are added, while precipitation changes are adjusted using a multiplicative factor. The result is a new scenario with mean and variability parameters adjusted according to the imposed changes but maintaining the historical signature of local differences between the true and theoretical distributions. This distribution stretching leads to the time-series presented in Figs. 7e and f, which demonstrates increased variability but also reflects how more extreme climate events change at a greater rate than the rate at which average events change.

At present the GCM treatment of rainfall intensity is subject to strong biases (e.g., from convective parameterizations required by GCM coarse resolutions; Flato *et al.*, 2013), so AgMIP regional integrated assessments have assumed no change in the shape parameter for future scenarios. As GCMs improve and regional climate models (RCMs) are increasingly available (e.g., from CORDEX; Giorgi *et al.*, 2006) and bring increased resolution of extreme events, more confidence may be placed in variability changes incorporated into AgMIP's mean and variability change scenarios. Future research is needed to determine if some combination of GCM-derived mean changes and RCM-derived variability changes may hold promise (particularly if uncertainty could be consistently gauged, as has been proposed in CORDEX), as this would draw a temporal scale from each model that was more suited to its native resolution.

Applications of Climate Datasets and Products

Ongoing applications within AgMIP

The climate datasets and scenario methodologies created for integrated assessment have also led to other applications. The delta methodology facilitated the creation of sensitivity tests for the various crop model intercomparison pilots (Asseng *et al.*, 2013; Bassu *et al.*, 2014; Li *et al.*, 2014), including a scenario in which a week of consecutive 35°C T_{max} was imposed at the common dates of wheat anthesis to allow the AgMIP Wheat Pilot Team to investigate heat stress impacts on fertility across participating models. Sensitivity tests are also the underlying basis for the impacts response surface protocols created for C3MP (Ruane *et al.*, 2014; see also Part 1, Chapter 8 in this volume), which allows the projected temperature and rainfall changes from any GCM to be matched with its RCP CO_2 concentration to estimate yield impacts across a global network of sites.

AgMERRA and AgCFSR are integral components of AgMIP's historical period intercomparison of global gridded crop models (see Part 1, Chapter 7 in this volume). These intercomparisons help gauge climate data uncertainties (see Part 1, Chapter 9

in this volume) and serve as a lens to reveal climate differences that are important to agricultural impacts. In these ways collaboration between climate and agronomy experts is mutually beneficial in prioritizing aims for future agricultural model and climate product development.

Applications in development

In the course of conducting the AgMIP regional integrated assessments, several high-priority research areas emerged for continuing development.

Near-term climate scenarios (i.e., from 5–40 years in the future) span a time-scale needed by many economists and stakeholders; including, for example, decisions on plant breeding, development aid, and many infrastructure investments. This time-scale also corresponds with a predictability gap, as understanding of the climate system has not identified clear and predictable modes of variability that allow for precise near-term planning (Flato *et al.*, 2013). This limitation restricts our ability to provide dynamical predictions; however AgMIP researchers are now seeking to understand this time-period through a combination of historical trend analysis, longer-term GCM projections, and statistical extrapolation (e.g., Greene *et al.*, 2014). For these time-scales, some combination of statistical and dynamical methods may support improved risk-management decisions. Continuing collaboration with agricultural modelers will help identify the methods most able to capture important near-term agro-climatic extremes.

Weather generators continue to be an integral component of agricultural assessments, assisting in gap-filling of historical conditions and also creating the necessary iterations to assess variability within future climate conditions. As many weather generators were originally developed for a particular region or season or for use with a particular crop model, AgMIP is currently developing a weather-generator intercomparison. This protocol-based study will investigate the extent to which assumptions in any given weather generator enable or limit the breadth of its application, as well as developing practices that make best use of these tools.

Conclusions and Next Steps

AgMIP climate datasets and scenarios allow protocol-based agricultural-modeling activities across a wide range of disciplinary models, geographic regions, and temporal and spatial scales. These datasets and scenarios therefore form a starting point for coordinated regional and global assessments where consistency is important to assessment of international markets, comparative advantage, and the transfer

of adaptation strategies. Within any given region or specific application, alternative datasets and scenario generation methodologies may be compared to those described here. Over time, AgMIP will look to develop these additional products and incorporate new approaches to enable global coverage for improved agricultural assessment.

In future phases of AgMIP, we anticipate expanding current near-term climate change efforts and an increasing focus on extreme events, which stakeholders have labeled as high-priority topics for focused research. Extreme events are often highly localized in space and push observational networks, climate models, and scenario-generation methodologies to the limits of their functionality. Improved climate scenarios that capture the ways in which extreme conditions may be exacerbated by long-term climate changes would enable simulation of acute climate impacts that will likely motivate land-use and policy decisions.

Acknowledgements

We appreciate the feedback and inputs of all who have participated in AgMIP Climate Team activities, particularly climate experts at the AgMIP Global Workshops in Long Beach, San Antonio, Rome, and New York City as well as climate experts leading regional climate analyses in Sub-Saharan Africa and South Asia. We also thank Ken Boote and Peter Thorburn for providing crucial inputs from the crop modeling perspective, Cheryl Porter for helping us design AgMIP climate information to link with IT utilities, Adam Greeley and Soyee Chiu for their testing of early AgMIP methodologies, Arthur Greene for his contributions on near-term climate scenarios, and the AgMIP Principal Investigators (Cynthia Rosenzweig, Jim Jones, Jerry Hatfield, and John Antle) for helping to provide a forum for transdisciplinary research in agricultural impacts. Elements of this work were supported by the UK Department for International Development and the USDA-Agricultural Research Service; the NASA Earth Science Division, the NASA Gulf of Mexico Initiative (NNX10AO10G); the NASA Modeling, Analysis, and Prediction Program; and the Committee on Earth Observing Satellites (CEOS). We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Table 1 of this chapter) for producing and making available their model output. For CMIP, the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

Annex 1: The AgMIP Climate Data Format

Table A.1. Example of the AgMIP climate data format. USAMCAXA indicates that this is a delta (mean-change-only) scenario for Ames, Iowa (USA), representing the RCP4.5 near-term (2010–2039) period from the ACCESS-1.0 GCM.

@DATE	YYYY	MM	DD	SRAD	TMAX	TMIN	RAIN	WIND	DEWP	VPRS	RHUM
1980001	1980	1	1	1.2	1.3	−1.5	0.0	3.1	−0.3	6.0	89
1980002	1980	1	2	4.7	−0.3	−2.6	0.0	4.9	−7.6	3.5	58
1980003	1980	1	3	1.9	−0.3	−4.8	0.0	4.3	−9.0	3.1	52
1980004	1980	1	4	3.8	0.2	−2.6	0.0	4.1	−5.2	4.2	67
1980005	1980	1	5	1.0	0.2	−3.2	1.5	3.4	−2.5	5.1	82
1980006	1980	1	6	8.5	1.9	−7.0	2.1	9.1	−0.8	5.7	82
1980007	1980	1	7	6.7	−6.4	−15.9	0.0	8.2	−13.4	2.2	58
1980008	1980	1	8	6.7	−8.7	−16.5	0.0	2.9	−17.1	1.6	51
1980009	1980	1	9	2.2	−11.4	−20.4	1.5	3.7	−16.2	1.8	68
1980010	1980	1	10	8.0	6.3	−13.7	0.0	8.0	5.3	8.9	93
1980011	1980	1	11	4.0	11.3	−9.8	0.0	11.9	7.3	10.2	76
1980012	1980	1	12	8.6	0.8	−13.7	0.0	6.1	−10.4	2.8	43
1980013	1980	1	13	8.6	12.5	1.3	0.0	6.7	2.4	7.3	50
1980014	1980	1	14	2.1	6.9	−3.2	0.0	4.1	−1.0	5.7	57
1980015	1980	1	15	1.0	8.6	4.6	0.0	4.1	7.2	10.2	91
1980016	1980	1	16	1.9	7.5	2.4	24.4	5.6	7.4	10.3	99
1980017	1980	1	17	3.7	2.5	−2.6	1.2	5.6	−0.6	5.9	80
1980018	1980	1	18	1.4	1.3	−3.2	0.0	2.7	1.2	6.6	99
1980019	1980	1	19	1.3	1.3	−4.3	2.1	4.3	−0.0	6.1	91
1980020	1980	1	20	3.1	1.3	−8.2	0.0	2.1	−6.1	3.9	58
1980021	1980	1	21	10.4	1.3	−7.0	0.0	4.2	−0.0	6.1	91
1980022	1980	1	22	8.8	1.9	−5.4	0.0	8.2	−1.2	5.6	80
1980023	1980	1	23	2.9	−4.2	−10.9	0.0	4.0	−13.4	2.2	49
1980024	1980	1	24	5.0	6.9	−7.0	0.0	5.7	3.9	8.1	81
1980025	1980	1	25	6.9	5.8	−4.8	0.0	5.9	3.5	7.8	85
1980026	1980	1	26	7.5	−4.2	−14.3	0.0	6.1	−11.5	2.6	57
1980027	1980	1	27	5.9	−9.8	−13.2	0.0	4.5	−16.2	1.8	60
1980028	1980	1	28	9.0	−8.7	−12.6	0.0	4.6	−14.7	2.0	62
1980029	1980	1	29	4.8	−9.2	−16.5	0.0	3.8	−14.6	2.0	65
1980030	1980	1	30	12.7	−9.8	−12.6	1.5	4.7	−12.6	2.3	80
1980031	1980	1	31	4.7	−10.9	−19.8	0.0	3.8	−13.2	2.2	83
1980032	1980	2	1	6.7	−8.5	−22.8	0.0	3.0	−11.4	2.6	80
...											
2010361	2010	12	27	3.5	1.1	−0.3	0.0	2.0	−0.8	5.8	87
2010362	2010	12	28	4.8	1.7	−0.1	9.0	1.4	−0.7	5.8	84
2010363	2010	12	29	3.3	2.8	1.5	2.8	4.2	1.8	7.0	93
2010364	2010	12	30	2.6	4.0	1.7	0.0	5.1	2.0	7.1	87
2010365	2010	12	31	3.4	1.3	−1.5	0.9	5.3	−2.5	5.1	76

*WEATHER DATA : USAMCAXA — baseline dates maintained for leap-year consistency

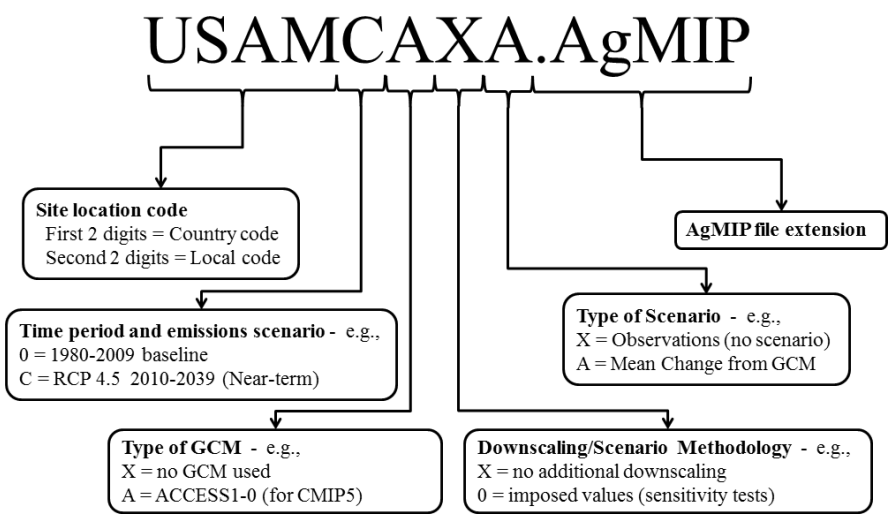


Fig. A.1. Definitions of the different components of the AgMIP climate file-naming convention. The first two digits identify the country as defined by the internet code (see http://www.web-l.com/country-codes). The second two digits are user-defined and are used to identify the site location. The fifth to eighth digits are used to convey specific information about the climate data for the specified site location (from Ruane and Hudson, 2013).

References

Allen, R. G., Pereira, L. S., Raes, D., and Smith, M. (1998). Crop Evapotranspiration – Guidelines for computing crop water requirements, *FAO Irrigation and Drainage Papers*, **56**, 333.

Arora, V. K., Scinocca, J. F., Boer, G. J., Christian, J. R., Denman, K. L., Flato, G. M., Kharin, V. V., Lee, W. G., and Merryfield, W. J. (2011). Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases, *Geophys. Res. Lett.*, **38**, L05805.

Asseng, S., Ewert F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**(9), 827–832.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K. J., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A. R., Kersebaum, K. C., Kim, S.-H., Kumar, N. S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M. V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., and Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors?, *Global Change Biol.*, **20**(7), 2301–2320.

Bi, D., Dix, M., Marsland, S., O'Farrell, S., Rashid, H., Uotila, P., Hirst, A., Kowalczyk, E., Golebiewski, M., Sullivan, A., Yan, H., Hannah, N., Franklin, C., Sun, Z., Vohralik, P., Watterson,

I., Zhou, X., Fiedler, R., Collier, M., Ma, Y., Noonan, J., Stevens, L., Uhe, P., Zhu, H., Griffies, S., Hill, R., Harris, C., and Puri, K (2013). The ACCESS Coupled Model: Description, control climate and evaluation, *Aust. Meteorol. Oceanogr. J.*, **63**, 41–64.

Bureau of Reclamation (2013). *Downscaled CMIP3 and CMIP5 Climate Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs*, U. S. Department of the Interior, Bureau of Reclamation, Technical Service Center, Denver, Colorado, p. 116. Available at: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/techmemo/downscaled_climate.pdf. Accessed on 30 September 2014.

Collins, W. J., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C. D., Joshi, M., Liddicoat, S., Martin, G., O'Connor, F., Rae, J., Senior, C., Sitch, S., Totterdell, I., Wiltshire, A., and Woodward, S (2011). Development and evaluation of an Earth-System model-HadGEM2, *Geosci. Model Dev.*, **4**(4), 1051–1075.

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., and Pasteris, P. A. (2008). Physiographically-sensitive mapping of temperature and precipitation across the conterminous United States, *Int. J. Climatol.*, **28**, 2031–2064.

Delworth, T. L., Rosati, A., Anderson, W., Adcroft, A. J., Balaji, V., Benson, R., Dixon, K., Griffies, S. M., Lee, H. C., Pacanowski, R. C., Vecchi, G. A., Wittenberg, A. T., Zeng, F. R., and Zhang, R. (2012). Simulated climate and climate change in the GFDL CM2.5 high-resolution coupled climate model, *J. Clim.*, **25**(8), 2755–2781.

Deser, C., Phillips, A. S., Tomas, R. A., Okumura, Y. M., Alexander, M. A., Capotondi, A., Scott, J. D., Kwon, Y. O., and Ohba, M. (2012). ENSO and Pacific decadal variability in the Community Climate System Model Version 4, *J. Clim.*, **25**(8), 2622–2651.

Dix, M., Vohralik, P., Bi, D., Rashid H., Marsland, S., O'Farrell, S., Uotila, P., Hirst, T., Kowalczyk, E., Sullivan, A., Yan, H., Franklin, C., Sun, Z., Watterson, I., Collier, M., Noonan, J., Rotstayn, L., Stevens, L., Uhe, P., and Puri K. (2013). The ACCESS coupled model: Documentation of core CMIP5 simulations and initial results, *Aust. Meteorol. Oceanogr. J.*, **63**, 83–99.

Dufresne, J.-L., Foujols, M.-A., Denvil, S., Caubel, A., Marti, O., Aumont, O., Balkanski, Y., Bekki, S., Bellenger, H., Benshila, R., Bony, S., Bopp, L., Braconnot, P., Brockmann, P., Cadule, P., Cheruy, F., Codron, F., Cozic, A., Cugnet, D., de Noblet, N., Duvel, J.-P., Ethé, C., Fairhead, L., Fichefet, T., Flavoni, S., Friedlingstein, P., Grandpeix, J.-Y., Guez, L., Guilyardi, E., Hauglustaine, D., Hourdin, F., Idelkadi, A., Ghattas, J., Joussaume, S., Kageyama, M., Krinner, G., Labetoulle, S., Lahellec, A., Lefebvre, M.-P., Lefevre, F., Levy, C., Li, Z. X., Lloyd, J., Lott, F., Madec, G., Mancip, M., Marchand, M., Masson, S., Meurdesoif, Y., Mignot, J., Musat, I., Parouty, S., Polcher, J., Rio, C., Schulz, M., Swingedouw, Szopa, D. S., Talandier, C., Terray, P., and Viovy, N. (2012). Climate change projections using the IPSL-CM5 Earth System Model: From CMIP3 to CMIP5, *Clim. Dyn.*, **40**(9–10), 2123–2165.

Dunn, R. J. H., Willett, K. M., Thorne, P. W., Woolley, E. V., Durre, I., Dai, A., Parker, D. E., and Vose, R. S. (2012). HadISD: a quality-controlled global synoptic report database for selected variables at long-term stations from 1973–2011, *Clim. Past*., **8**(5), 1649–1679.

Dunne, J. P., John, J., Adcroft, A., Griffies, S. M., Hallberg, R. W., Shevliakova, E., Stouffer, R. J., Cooke, W. F., Dunne, K. A., Harrison, M. J., Krasting, J. P., Malyshev, S., Milly, P. C. D., Phillipps, P., Sentman, L. T., Samuels, B. L., Spelman, M. J., Winton, M., Wittenberg, A. T, and Zadeh, N. (2012). GFDL's ESM2 global coupled climate-carbon Earth System Models Part I: Physical formulation and baseline simulation characteristics, *J. Clim.*, **25**(19), 6646–6666.

Dunne, J. P., John, J., Shevliakova, E., Stouffer, R.J., Krasting, J. P., Malyshev, S., Milly, P. C. D., Sentman, L. T., Adcroft, A., Cooke, W. F., Dunne, K. A., Griffies, S. M., Hallberg, R. W., Harrison, M. J., Levy II, H., Wittenberg, A. T., Phillipps, P., and Zadeh, N. (2013). GFDL's ESM2 global coupled climate-carbon Earth System Models Part II: Carbon system formulation and baseline simulation characteristics, *J. Clim.*, **26**(7), 2247–2267.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., Cox P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., and Rummukainen, M. (2013). "Evaluation of Climate Models", in Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

Gent, P. R., Danabasoglu, G., Donner, L. J., Holland, M. M., Hunke, E. C., Jayne, S. R., Lawrence, D. M., Neale, R., Rasch, P. J., Vertenstein, M., Worley, P., Yang, Z. L., and Zhang, M. (2011). The Community Climate System Model Version 4, *J. Clim.*, **24**(19), 4973–4991.

Giorgetta, M. A., Jungclaus, J., Reick, C. H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Ilyina, T., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., Mikolajewicz, U., Mueller, W., Notz, D., Pithan, F., Raddatz, T., Rast, S., Redler, R., Roeckner, E., Schmidt, H., Schnur, R., Segschneider, J., Six, K. D., Stockhause, M., Timmreck, C., Wegner, J., Widmann, H., Wieners, K.-H., Claussen, M., Marotzke, J., and Stevens, B. (2014). Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the Coupled Model Intercomparison Project phase 5, *J. Adv. Model. Earth Syst.*, **5**(3), 572–597.

Giorgi, F., Jones, C., and Asrar, G. R., (2009). Addressing climate information needs at the regional level: the CORDEX framework, *WMO Bulletin*, **58**(3), 175–183.

Glotter, M., Elliott, J., McInerney, D., Best, N., Foster, I., and Moyer, E. J. (2014). Evaluating the utility of dynamical downscaling in agricultural impacts projections, *Proc. Natl. Acad. Sci. U.S.A.*, **111**(24), 8776–8781.

Greene, A., Goddard, L., Gonzalez, P. L. M., Ines, A., and Chryssanthacopoulos, J. (2014). A climate generator for agricultural planning in southeastern South America, *Agric. Forest Meteorol.*, in press.

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H. (2013). Updated high-resolution grids of monthly climatic observations — the CRU TS3.10 Dataset, *Int. J. Climatol.*, **34**(3).

Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D., and New, M. (2008). A European daily high-resolution gridded dataset of suface temperature and precipitation, *J. Geophys. Res.* **113**, D20119.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas, *Int. J. Climatol.*, **25**(15), 1965–1978.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J. (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Hsu, K. L., Gao, X. G, Sorooshian, S., and Gupta, H.V. (1997). Precipitation estimation from remotely sensed information using artificial neural networks, *J. Appl. Meteorol.*, **36**(9), 1176–1190.

Huffman, G. J., Adler, R. F., Bolvin, D. T., Gu, G., Nelkin, E. J., Bowman, K. P., Hong, Y., Stocker, E. F., and Wolff, D. B. (2007). The TRMM multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales, *J. Hydrometeorol.*, **8**(1), 38–55.

Huffman, G. J., Adler, R. F., Bolvin, D. T., and Gu, G. (2009). Improving the global precipitation record: GPCP version 2.1, *Geophys. Res. Lett.*, **36**, L17808.

Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., Lamarque, J.-F., Large, W. G., Lawrence, D., Lindsay, K., Lipscomb, W. H., Long, M. C., Mahowald, N., Marsh, D. R., Neale, R.B., Rasch, P., Vavrus, S., Vertenstein, M., Bader, D., Collins, W. D., Hack, J. J., Kiehl, J., and Marshall S. (2013). The Community Earth System Model: A framework for collaborative research, *Bull. Am. Meteorol. Soc.*, **94**(9), 1339–1360.

Irving, D. B., Perkins, S. E., Brown, J. R., Sen Gupta, A., Moise, A. F., Murphy, B. F., Muir, L. C., Colman, R. A., Power, S. B., Delage, F. P., and Brown, J. N. (2011). Evaluating global climate models for the Pacific island region, *Clim. Res.*, **49**(3), 169–187.

Iversen, T., Bentsen, M., Bethke, I., Debernard, J. B, Kirkevag, A., Seland, O., Drange, H., Kristjansson, J. E., Medhaug, I., Sand, M., and Seierstad, I. A. (2013). The Norwegian Earth System Model, NorESM1-M. Part 2: Climate response and scenario projections, *Geosci. Model Dev.*, **6**(2), 389–415.

Ji, D., Wang, L., Feng, J., Wu, Q., Cheng, H., Zhang, Q., Yang J., Dong, W., Dai, Y., Gong, D., Zhang, R.-H, Wang, X., Liu, J., Moore, J. C., Chen, D., and Zhou, M. (2014). Description and basic evaluation of BNU-ESM version 1, *Geosci. Model Dev. Discuss.*, **7**, 1601–1647.

Joyce, R. J., Janowiak, J. E., Arkin, P. A., and Xie, P. (2004). CMORPH: a method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution, *J. Hydrometeorol.*, **5**(3), 487–503.

Kripalani, R. H., Oh, J. H., Kulkarni, A., Sabade, S. S., and Chaudhari, H. S. (2007). South Asian summer monsoon precipitation variability: Coupled climate model simulations and projections under IPCC AR4, *Theor. Appl. Climatol.*, **90**(3–4), 133–159.

Li, T., Hasegawa, T., Yin, X., Zhu, Y., Boote, K. J., Adam, M., Buis, S., Confalonieri, R., Fumoto, T., Gaydon, D., Marcaida, M., Oriol, P., Ruane, A. C., Ruget, F., Singh, B., Singh, U., Tang, L., Tao, F., Yoshida, H., Zhang, Z., and Bouman, B. (2014). Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions, *Global Change Biology*, in press.

Long, M. C., Lindsay, K., Peacock, S., Moore, J. K., and Doney, S. C. (2013). Twentieth-century oceanic carbon uptake and storage in CESM1(BGC), *J. Clim.*, **26**(18), 6775–6880.

Martin, G. M., Bellouin, N., Collins, W. J., Culverwell, I. D., Halloran, P. R., Hardiman, S. C., Hinton, T. J., Jones, C. D., McDonald, R. E., McLaren, A. J., O'Connor, F. M., Roberts, M. J., Rodriguez, J. M., Woodward, S., Best, M. J., Brooks, M. E., Brown, A. R., Butchart, N., Dearden, C., Derbyshire, S. H., Dharssi, I., Doutriaux-Boucher, M., Edwards, J. M., Falloon, P. D., Gedney, N., Gray, L. J., Hewitt, H. T., Hobson, M., Huddleston, M. R., Hughes, J., Ineson, S., Ingram, W. J., James, P. M., Johns, T. C., Johnson, C. E., Jones, A., Jones, C. P., Joshi, M. M., Keen, A. B., Liddicoat, S., Lock, A. P., Maidens, A. V., Manners, J. C., Milton, S. F., Rae, J. G. L., Ridley, J. K., Sellar, A., Senior, C. A., Totterdell, I. J., Verhoef, A., Vidale, P. L., and Wiltshire, A. (2011). The HadGEM2 family of Met Office Unified Model climate configurations, *Geophys. Model Dev.*, **4**(3), 723–757.

Mearns, L. O., Giorgi, F., Whetton, P., Pabon, D., Hulme, M., and Lal, M. (2003). *Guidelines for use of climate scenarios developed from regional climate model experiments*, Data Distribution Centre of the Intergovernmental Panel on Climate Change, Geneva, Switzerland, p. 38.

Mearns, L. O., Gutowski, W. J., Jones, R., Leung, L.-Y., McGinnis, S., Nunes, A. M. B., and Qian, Y. (2009). A regional climate change assessment program for North America, *Eos Trans. AGU*, **90**(36), 311–312.

Meehl, G. A., Arblaster, J. M., Caron, J. M., Annamalai, H., Jochum, M., Chakraborty, A., and Murtugudde, R. (2012). Monsoon Regimes and Processes in CCSM4. Part I: The Asian–Australian Monsoon, *J. Clim.*, **25**(8), 2583–2608.

Monfreda C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, *Global Biogeochem Cy.*, **22**(1), pp. 1–19.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grübler, A., Jung, T. Y., Kram, T., La Rovere, E. L., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Riahi, K., Roehrl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M., Shukla, P., Smith, S., Swart, R., van Rooijen, S., Victor, N., and Dadi, Z. (2000). *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, p. 599.

Reichle, R. H., Koster, R. D., De Lannoy, G. J. M., Forman, B. A., Liu, Q., Mahanama, S. P. P., and Touré, A. (2011). Assessment and enhancement of MERRA land surface hydrology estimates, *J. Clim.*, **24**(24), 6322–6338.

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M. G., Schubert, S. D., Takacs, L., Kim, G. K., Bloom, S., Chen, J. Y., Collins, D., Conaty, A., da Silva, A., Gu, W., Joiner, J., Koster, R. D., Lucchesi, R., Molod, A., Owens, T., Pawson, S., Pegion, P., Redder, C. R., Reichle, R., Robertson, F. R., Ruddick, A. G., Sienkiewicz, M., and Woollen, J. (2011). MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, *J. Clim.*, **24**(14), 3624–3648.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Rotstayn, L. D., Jeffrey, S. J., Collier, M. A., Dravitzki, S. M., Hirst, A. C., Syktus, J. I., and Wong, K. K. (2012). Aerosol- and greenhouse gas-induced changes in summer rainfall and circulation in the Australasian region: A study using single-forcing climate simulations. *Atmos. Chem. Phys.*, **12**(14), 6377–6404.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. *Agr. Forest Meteorol.*, in press.

Ruane, A. C. and Hudson, N. I. (2013). *Guide for Running AgMIP Climate Scenario Generation Tools with R in Windows, Version 2.3*. Available at: http://www.agmip.org/wp-content/uploads/2013/10/Guide-for-Running-AgMIP-Climate-Scenario-Generation-with-R-v2.3.pdf. Accessed on 4 June 2014.

Ruane, A. C., McDermid, S., Rosenzweig, C., Biagorria, G. A., Jones, J. W., Romero, C. C., and Cecil, L. D. (2014). Carbon-Temperature-Water change analysis for peanut production under climate change: a prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP), *Global Change Biol.*, **20**(2), 394–407.

Sabade, S. S., Kulkarni, A., and Kripalani, R. H. (2010). Projected changes in South Asian summer monsoon by multi-model global warming experiments, *Theor. Appl. Climatol.*, **103**(3–4), 543–565.

Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., and Ziese, M. (2011). *GPCC Full Data Reanalysis Version 6.0 at 0.5°: Monthly Land-Surface Precipitation from Rain-Gauges built on GTS-based and Historic Data*. Available at: http://dx.doi.org/10.5676/DWD_GPCC/FD_M_V6_050. Accessed 30 September 2014.

Stackhouse, P. W. Jr., Gupta, S. K., Cox S. J., Mikovitz J. C., Zhang, T., and Hinkelman, L. M. (2011). The NASA/GEWEX Surface Radiation Budget Release 3.0: 24.5-Year Dataset, *GEWEX News*, **21**(1), 10–12.

Steduto, P., Hsiao, T. C., Raes, D., and Fereres, E. (2009). AquaCrop: a new model for crop prediction under water-deficit conditions, *Options Méditerranéennes, Ser. A*, **80**, 285–292.

Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design, *Bull. Am. Meteorol. Soc.*, **93**(4), 485–498.

van der Linden, P. and Mitchell, J. F. B. (2009) *ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project*, Met Office Hadley Centre, Exeter, UK.

Volodin, E. M., Dianskii, N. A., and Gusev, A. V. (2010). Simulating present-day climate with the INMCM4.0 coupled model of the atmospheric and oceanic general circulations, *Izvestiya Atmos. Ocean. Phys.*, **46**(4), 414–431.

von Salzen, K., Scinocca, J. F., McFarlane, N. A., Li, J., Cole, J. N. S., Plummer, D., Verseghy, D., Reader, M. C., Ma, X., Lazare, M., and Solheim, L. (2013). The Canadian Fourth Generation Atmospheric Global Climate Model (CanAM4). Part I: Representation of physical processes, *Atmos. Ocean*, **51**(1), 104–125.

Watanabe, M., Chikira, M., Imada, Y., and Kimoto, M. (2011). Convective control of ENSO simulated in MIROC. *J. Clim.*, **24**(2), 543–562.

Watanabe, M., Suzuki, T., O'ishi, R., KomuroY., Watanabe, S., Emori, S., Takemura, T., Chikira ,M., Ogura, T., Sekiguchi, M., Takata, K., Yamazaki, D., Yokohata, T., Nozawa, T., Hasumi, H., Tatebe, H., and Kimoto, M. (2010). Improved climate simulation by MIROC5: mean states, variability, and climate sensitivity, *J. Clim.*, **23**(23), 6312–6335.

White, J. W., Hoogenboom, G., Kimball, B. A., and Wall, G. W. (2011). Methodologies for simulating impacts of climate change on crop production, *Field Crops Res.* **124**, 357–368.

White, J. W., Hoogenboom, G., Wilkens, P. W., Stackhouse, P. W., and Hoel, J. M. (2011). Evaluation of Satellite-Based, Modeled-Derived Daily Solar Radiation Data for the Continental United States, *Agron. J.*, **103**(4), 1242–1251.

Wilby, R. L., Charles, S., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. O. (2004). *Guidelines for use of climate scenarios developed from statistical downscaling methods*, IPCC Supporting Material. Available at: www.ipcc-data.org/guidelines/dgm_no2_v1_09_2004.pdf. Accessed 30 September 2014.

Wilks, D. S. (2010). Use of stochastic weather generators for precipitation downscaling, *WIREs Clim. Change*, **1**, 898–907.

Wilks, D. S. (2011). *Statistical Methods in the Atmospheric Sciences*, 3rd ed., Academic Press, San Diego.

Wilks, D. S. (2012). Stochastic weather generators for climate-change downscaling, part II: multivariable and spatially coherent multisite downscaling, *WIREs Clim. Change*, **3**, 267–278.

Willmott, C. J. and Matsuura, K. (1995). Smart Interpolation of Annually Averaged Air Temperature in the United States, *J. Appl. Meteorol.*, **34**(12), 2577–2586.

WMO (1989). *Calculation of Monthly and Annual 30-Year Standard Normals (WCDP928 No.10, WMO-TD/No.341)*, World Meteorological Organization, Geneva.

Wu, T. (2012). A mass-flux cumulus parameterization scheme for large-scale models: Description and test with observations, *Clim. Dyn.*, **38**(3–4), 725–744

Xin, X., Zhang, L., Zhang, J., Wu, T., and Fang, Y. (2013). Climate change projections over East Asia with BCC_CSM1.1 climate model under RCP scenarios, *J. Meteorol. Soc. Jpn.*, **91**(4), 413–429.

Yatagai, A., Kamiguchi, K., Arakawa, O., Hamada, A., Yasutomi, N., and Kitch, A., (2012). APHRODITE: Constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges, *Bull. Amer. Meteor. Soc.*, **93**, 1401–1415.

Yukimoto, S., Yoshimura, H., Hosaka, M., Sakami, T., Tsujino, H., Hirabara, M., Tanaka, T. Y., Deushi, M., Obata, A., Nakano, H., Adachi, Y., Shindo, E., Yabu, S., Ose, T., and Kitoh, A. (2011). *Meteorological Research Institute-Earth System Model v1 (MRI-ESM1)—Model Description*, Technical Reports of the Meteorological Research Institute, **64**, p. 88.

Yukimoto, S., Adachi, Y., Hosaka, M., Sakami, T., Yoshimura, H., Hirabara, M., Tanaka, T. Y., Shindo, E., Tsujino, H., Deushi, M., Mizuta, R., Yabu, S., Obata, A., Nakano, H., Koshiro, T., Ose, T., and Kitoh, A. (2012). A New Global Climate Model of the Meteorological Research Institute: MRI-CGCM3-Model Description and Basic Performance, *J. Meteor. Soc. Jpn.*, **90A**, 23–64.

Chapter 4

Cropping Systems Modeling in AgMIP: A New Protocol-Driven Approach for Regional Integrated Assessments

Peter J. Thorburn[1], Kenneth J. Boote[2], John N. G. Hargreaves[3], Perry L. Poulton[3], and James W. Jones[2]

[1]*Commonwealth Scientific and Industrial Research Organisation Agriculture Flagship, Brisbane, Australia*

[2]*University of Florida, Gainesville, FL, USA*

[3]*Commonwealth Scientific and Industrial Research Organisation Agriculture Flagship, Toowoomba, Australia*

Introduction

As the global climate continues to change, agriculture and food supply will be increasingly affected (Hillel and Rosenzweig, 2012). Studies of climate change impact are important both to understand the magnitude of the effect, and to develop strategies to adapt to the changing climate. Increasingly, these studies will need to integrate multiple information sources about possible future climates, climate–agriculture interactions, and economic drivers for, and consequences of the impacts and adaptation strategies. In short, the studies will be integrated climate change impact assessments, ideally conducted on a regional scale to capture regional variations in climate, soils, agriculture, and economics.

There have been numerous climate change impact assessments undertaken in the past. These studies have used different climate scenarios, different approaches to defining and modeling agricultural systems, and different economic assumptions. As a result, it is difficult to compare the results of these studies (Rosenzweig *et al.*, 2013). Additionally, uncertainty has often only been explicitly addressed in climate projections through the use of ensembles of global climate models (GCMs): Uncertainties in other aspects of the integrated system have been overlooked, including the variability contributed by the uncertainty of climate response of different multiple agroecosystem models. To understand more fully the effects of climate change

on agriculture, we need studies that have been undertaken by using a consistent methodology with a more complete representation of uncertainty in all sectors of the system.

The Agricultural Model Intercomparison and Improvement Project (AgMIP) is a major international effort that aims to address these challenges in understanding the effects of climate change on agriculture, and produce improved projections of climate impacts on the agricultural sector. Studies undertaken within AgMIP both employ standardized methodologies and use ensembles of models for both climate and crop modeling. The standardization of AgMIP integrated assessment studies facilitates comparison between studies, providing a more complete picture of climate change impacts and adaptations across study regions. AgMIP studies also provide a more complete understanding of the uncertainty in the projected outcomes. This chapter describes the methodologies developed for crop modeling in AgMIP. It also discusses some of the problems encountered in application of the standardized methodology and recommends potential future improvements.

Begin at the End — What Information is Needed from the Crop Models?

AgMIP studies seek to answer three core questions (see Part 1, Chapter 2 in this volume):

1. What is the sensitivity of current agricultural production systems to climate change?
2. What is the impact of climate change on future agricultural production systems?
3. What are the benefits of climate change adaptations?

Answering these questions requires crop models that have been set up to represent accurately the cropping systems of the region being studied, climate information that will drive the processes in the crop model, and data/information on farms in the region (Fig. 1). The farm-level data describes crop management strategies, soils, etc., and, to address Core Question 3, relevant adaptation strategies. Adaptation strategies and their economic value are informed by representative agricultural pathways (RAPs), which provide an overall narrative description of a plausible future development pathway for agriculture in a region, and also contain key variables with qualitative storylines and quantitative trends, that are consistent with higher-level drivers (see Part 1, Chapter 5 in this volume).

Outputs from the crop models are used in the economic analyses, which are undertaken with the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD model; Antle, 2011). The TOA-MD model uses data from

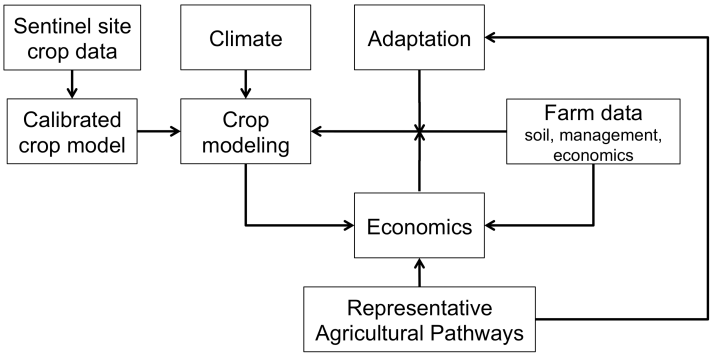


Fig. 1. Flow diagram of the different components of an integrated climate change impact assessment in AgMIP.

farm surveys on crop production and economic factors that determine the economic impacts of future production systems (defined in terms of climate, crops, and management) compared with current systems. From a crop production perspective, addressing the three AgMIP core questions in the TOA-MD model requires a prediction of how crop production will change as a result of projected climate change and technology trends identified in the RAPs. The effects of the drivers on crop production are captured through the ratio of future to current production rather than a prediction of future crop production in absolute terms. More formally, the ratio (R) of future to current yields (Y) is:

$$R = Y_{\text{future}} / Y_{\text{current}} \tag{1}$$

The yields currently being achieved by farmers in a region are multiplied by R to predict the future yields in the different scenarios being considered. Crop models generally over-predict yields because there are many factors in farmers' fields that reduce yields (e.g., suboptimal management, pests, and diseases) which are not represented in the models. The use of the parameter R in the TOA-MD model potentially reduces the error in crop model predictions, provided the errors in simulating current production systems are similar to those in predicting future systems, with the added assumption that the crop models have the correct sensitivity to climate change factors. Thus R is likely to be a more stable output parameter from crop models than the predicted yields themselves.

A value of R is needed for all crops, crop models, farms, climates, RAPs, and adaptations. Given that there will be multiple crops grown in a region, each being modeled with more than one crop model, that regions will contain many farms, and that there will be a range of climate change projections, RAPS, and adaptations, undertaking crop modeling in an AgMIP regional assessment is a significant task in computation and information management.

Setting Up the Crop Models

Crop growth and yield is determined by site factors (weather and soils), management (e.g., sowing date, fertilization, cultivation, etc.), crop genetics (i.e., crop cultivar), and pests and diseases. The first three of these are represented in all well-developed crop models. The algorithms representing these processes in the models contain many coefficients, of which the values need to be set. Some crop coefficients are specific to a species, others to a cultivar. Many coefficients that relate to soil processes are site specific. The values of all these coefficients need to be determined either by calibration (i.e., changing the coefficient value to get a fit to some other measured value) or parameterized from direct measurements (e.g., setting soil bulk density) to undertake the crop simulations for AgMIP climate change impact assessments. The main outputs from this stage of the crop modeling are well-calibrated cultivars and parameterized soils, and examples of the models being able to predict crop growth at experimental sites accurately (Fig. 2). Data from high-quality experiments are required to set up the crop models accurately.

Setting parameter values

A critical step in crop modeling is determining the phenology parameters for the important crops and cultivars in the region being studied. If previous crop modeling studies have been undertaken in the study region, some crop cultivars will have been parameterized. Parameters for other crop cultivars will need to be determined from available experimental data. Thus, it is important to obtain details of relevant experiments that have been conducted in the region being studied. Setting values of crop cultivars is usually done by calibration (e.g., varying thermal time to match

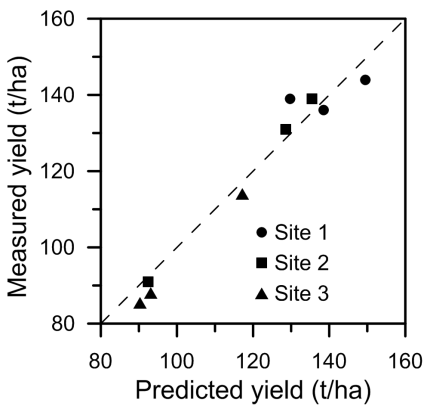


Fig. 2. Prediction of sugarcane yields over three years at three sites as an example of the output that results from the initial crop model "setup" activities in an AgMIP regional climate impact assessment (after Thorburn *et al*., 2011).

observed anthesis and maturity dates). Some models have in-built numerical optimizing tools to facilitate estimation of cultivar parameters (e.g., DSSAT; Jones *et al.*, 2011), while for others optimization procedures have been developed by users (e.g., Archontoulis *et al.*, 2014; see also Part 2, Chapter 10 in this volume). However, in many cases coefficient values have to be fitted "by eye".

Crop models also represent the effect of temperature on crop phenology and growth. Some of the functions that represent temperature were developed on data that spans a limited range of temperatures, and may not be accurate at temperatures outside (especially higher than) this range (Asseng *et al.*, 2013; Rötter *et al.*, 2011). If high temperatures occur in the study region, the effect of these temperatures on modeling crop growth needs to be considered. It is possible that crop cultivar parameters can be inappropriately adjusted in an attempt to overcome deficiencies in the underlying temperature-response algorithms in some models. In this situation, it may be better to change the temperature-response algorithm (see, for example, Part 2, Chapter 8 in this volume) before calibrating the cultivar parameters, especially if data are available over a wider range of temperature than just the regional sites. However, as crop models are further developed to represent climate change effects, the need to adjust temperature-response algorithms will decrease.

All well-developed crop models also represent soil-water dynamics, and the effect of water stress on crop growth. Likewise, many also represent soil-nitrogen cycling and crop-nitrogen stress. In these models, the basic structure and operation of the crop stress physiology and soil processes have been reasonably well tested, and applying these models in a region only requires that the parameters for the soil processes in the models are determined.

However, it may be valuable to test the crop and soil-water and/or nitrogen dynamics against experimental data to ensure the processes in the models are appropriate for the region being studied. Such testing is likely to be most beneficial for soil-nitrogen dynamics, particularly for evaluating the initialization of the soil-carbon pools in the nitrogen routines. Inappropriately initialized carbon pools will give too little or too much nitrogen mineralization during crop growth, which will result in inaccurate predicted responses to different rates of nitrogen fertilizer additions. This problem is particularly important with infertile soils where crops are grown with low nitrogen inputs. However, structure of soil-nitrogen submodels differ substantially among crop models (Fig. 3), and approaches to initializing carbon pools in them are not yet standardized (Basso *et al.*, 2011; Gabrielle *et al.*, 2002).

Data sources

Experiments are conducted for differing reasons. These reasons dictate the amount of information collected in the experiments, which in turn influences the purposes

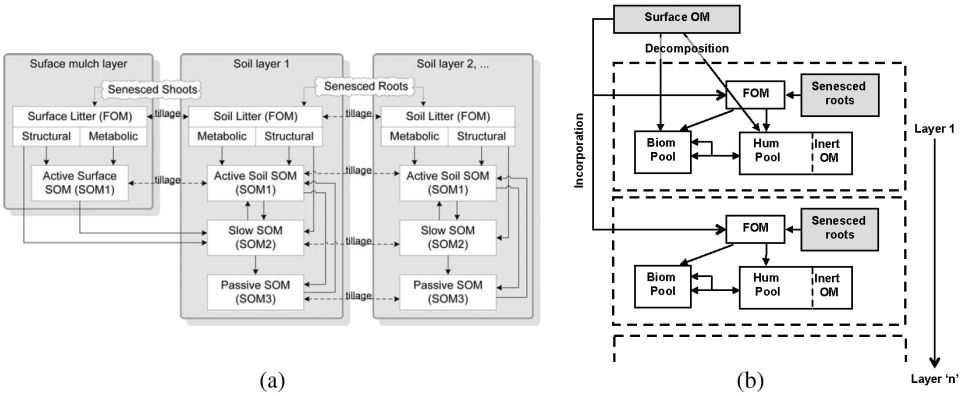


Fig. 3. Schematic representations of the soil-carbon pool structure in the nitrogen sub-models of DSSAT (left, after Porter *et al.*, 2010) and APSIM (right, after Thorburn *et al.*, 2005) models.

(other than those originally intended) for which the data can be used. In AgMIP, experimental sites or other well-characterized sites have been termed "sentinel sites" (Rosenzweig *et al.*, 2013). Sentinel sites can be ranked according to the comprehensiveness (i.e., quantity and quality) of the information collected there, from "platinum", the most comprehensive, through to "gold", "silver", and "copper", the least comprehensive. The attributes that distinguish between the different levels are described by Kersebaum *et al.* (2014).

Data from platinum sites would be suitable for developing phenological parameters for cultivars, as well as parameterizing and initializing soil-water and nitrogen models. If the experiment had a focus on nitrogen management (e.g., had treatments with different application rates of nitrogen fertilizer), the data may also be useful for testing the carbon pool initialization of the nitrogen submodels. Data from less-comprehensive experiments can be valuable for developing phenological parameters for cultivars, provided the appropriate phenological measurements were made and crops suffered no major stress (Jones *et al.*, 2011). For example, Zubair *et al.* (see Part 2, Chapter 10 in this volume) used crop breeders' variety evaluation trial results to supplement a small number of more detailed agronomic experiments to parameterize different rice cultivars growing in Sri Lanka.

Archiving data and simulation results

An important legacy of AgMIP projects is the creation of openly accessible data bases on crop performance in different regions under different climates and managements. The experimental data, model parameters, and simulation results from these activities should be entered into the AgMIP Crop Experiment (ACE) database. This database is one of a range of "IT tools" that have been developed within AgMIP

(see Part 1, Chapter 6 in this volume; see also the http://tools.agmip.org/ website) to facilitate the uniform formatting and storage of information, and provision of parameter files and initialization data for different crop models in the model-specific format.

Modeling Farms in the Region

Once the crop models have been successfully set up, cropping systems in the region can be simulated. Information needs to be obtained on these cropping systems, then this information will need to be converted into formats used by the different crop models so that standardized simulations can be run with multiple crop models.

Regional information derived from farm surveys — the "matched" case

The main information on which to base these cropping simulations will come from surveys of the agricultural systems being practiced by farms or households in the region. This situation is referred to as the "matched" case, since simulated crop yield outputs for the various weather, soil, and management for the surveyed farms can be "matched" (compared) with site-specific observed yields for each farm.

Economic information required for the TOA-MD model will be obtained from these surveys by economists (see Part 1, Chapter 5 in this volume), so collaborating with economists at this stage of an integrated assessment is beneficial. The aim is to obtain information from a significant number of (e.g., 50–200) farms in a region.

Certain information is critical to being able to simulate a farm (or fields in a farm), and is thus the minimum required from surveys. Critical information includes:

1. Site identifiers (also used to identify most appropriate weather station and soil type):
    a. Village name.
    b. Farm/field name.
    c. Latitude and longitude.
2. Crops grown and the "rules" farmers use to govern crop rotations.
3. Sowing dates (yyyy-mm-dd) for the crops grown.
4. Amount of mineral nitrogen (N) fertilizer amount used. Ideally this will be the mass of elemental N applied per ha. However, if that precision of information is not available it is important to obtain some estimate amounts, such as none, "low", "medium", and "high". (The definition of these classes need to be determined in collaboration with local agronomists or extension staff.).
5. Amount (kg DM/ha) of farmyard manure or organic matter applied.

6. Whether the farm is irrigated. If irrigated, information is needed on the total amount applied in a season and, ideally, the amount applied at each irrigation and the approach taken to scheduling irrigation.
7. Crop yield (dry weight/ha, or another measure that can be related to dry weight).

However, considerably more information is required to set up and run the crop models. This additional information includes:

8. Crop cultivar.*
9. Sowing date (yyyy-mm-dd).*
10. Sowing depth.
11. Plant population (i.e., plants/m^2).*
12. Maximum rooting depth (and the relative distribution of roots with increasing soil depth).
13. Timing of mineral N fertilizer applications (days after sowing or dates in yyyy-mm-dd), applied through split application (if so, the proportion in each split), etc.*
14. Timing of farmyard manure or organic matter applications (days after sowing or dates in yyyy-mm-dd).*
15. Management of residues from prior crop, whether harvested for another use, burnt, or left in the field (if the latter, the amount of residue, kg/ha).*
16. Information to initialize soil-water and -nitrogen submodels at the commencement of the simulation:
    a. Values of parameters for the soil-water submodels (Fig. 4).#
    b. Initial soil-water content (either as a proportion of a "full" profile or a volumetric water content for each soil layer).

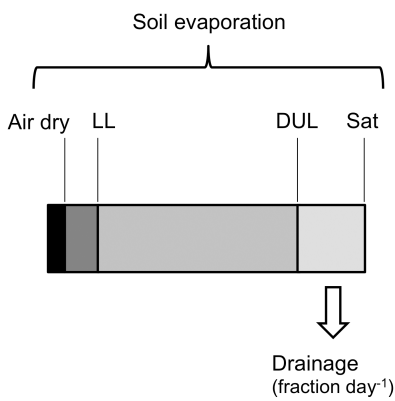


Fig. 4. Schematic representation of parameters commonly used in "cascading-bucket" water-balance submodels. LL is the lower limit, DUL is the drained upper limit, and Sat is saturation water content.

c. Initial soil-nitrate and -ammonium concentrations for each layer.
d. Total organic carbon and nitrogen in each soil layer[#], and the proportion of the carbon in the different carbon pools in the soil-nitrogen submodel.
e. Root residues from prior crops (kg/ha).

It is possible that some of this information (especially items in the list indicated by *) could be collected during the farm surveys, and carefully designing the surveys will be beneficial. Other information may be documented in, or derived from information in local soil surveys (particularly items in the list indicated by [#]). It is easier to simulate farming systems by using actual information rather than information derived from other sources (e.g., expert opinion), so it is beneficial to put a substantial effort into collecting as much information as possible. However, it will commonly be necessary to make assumptions regarding many of these initial conditions and management factors, ideally in collaboration with local extension staff, agronomists, and/or soil scientists. The assumptions made need to be separately documented along with the observed field survey data for each simulated result.

Preparing and running the simulations

The information (collected and derived) for 50–200 farms from the 16 items listed above produces a substantial amount of data, which has to subsequently be developed as inputs (site factors, crop management, and crop cultivar specifications) for the different models used in the regional impact assessment. There are AgMIP IT tools developed to facilitate the uniform formatting and storage of this information, and provision of parameter files and initialization data for the crop models in the model-specific format. A particularly useful tool is the Data Overlay for Multi-model Export (DOME), which facilitates provision of standardized information on assumptions associated with each crop model to simulate crop growth and yield. One feature of DOME is to provide model input information that is not contained in field surveys (or yield trials or even experiments). There is a file format within DOME that can be used to fill in required inputs that are missing so that all of the models make use of the same regional or site-specific assumptions. Some crop models have internal assumptions that provide missing inputs and with DOME this information can be used in all models to achieve better consistency. The use of DOME files ensures the integrity of observed values, clearly documenting assumptions made for simulation analyses, and it ensures consistency across crop models for multi-model applications.

Much of the information, especially that describing crop management, will be generic for many crop models, and so can be handled easily by DOME. Some model-specific information may still be used in multiple models. A good example is the

specification of parameters for the soil-water submodels. The "cascading bucket" approach (Fig. 4) is used in many water-balance submodels, so parameters such as LL, DUL, and saturation, once derived for a farm (or experimental site), can be used by all models with this type of soil-water submodel. The other approach to modeling soil water is based on Richards' equation. While the parameters used in Richards' equation are different from those in the "cascading-bucket" models, they can be derived from "cascading-bucket" parameters (Huth *et al.*, 2012) allowing parameterization of both types of submodels from common data. This conversion has not yet been implemented in the AgMIP IT tools.

Perhaps the most model-specific information is that used to initialize soil-nitrogen submodels. Most models will use information on total organic carbon to define the amount of organic matter in each soil layer, but the distribution of that organic matter between the different carbon pools in the model cannot be generalized between models that have different pool structures, e.g., DSSAT (Hoogenboom *et al.*, 2010) and APSIM, the two most widely used crop models (Fig. 3). There are also specific features of some cropping systems that are handled differently by different crop models; a good example being ponding in rice fields. Initializing soil-nitrogen submodels and specifying ponded rice systems currently needs to be done individually for each model.

Using the AgMIP IT tools to provide model inputs, crop yields are simulated for the survey farms based on the survey data and associated assumptions. When simulated with the weather data corresponding to the time-period of the survey, simulation results can be compared with the yields obtained in the survey (Fig. 5). This comparison provides an important opportunity to assess the accuracy of the

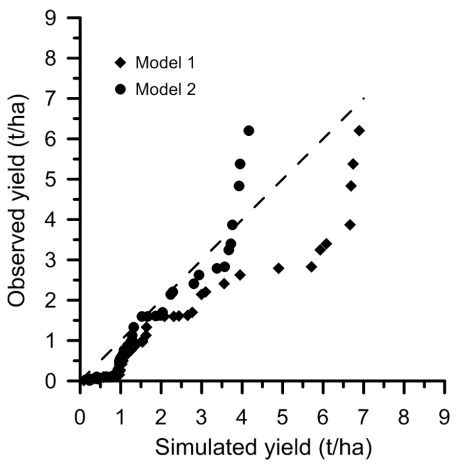


Fig. 5. Maize yields simulated by two crop models at 47 farms in the Machokas region, Kenya.

simulation. If yields of a local experiment were accurately simulated after the models were set up, errors in simulation of yields from local farms are likely due to errors in specification of the cropping system (e.g., planting date, cultivar, rates of N fertilizer) or the soil submodels, as well as factors (such as pests and diseases, soil salinity or acidity) that are not yet commonly considered in crop models. In the examples in Fig. 5, the inability of the models to simulate the high farm yields was likely due to inaccurate initialization of carbon pools in the soil-nitrogen submodel, which resulted in inaccurate mineralization of nitrogen relative to crop demands at farms with favorable weather for maize growth at the time of the simulation (i.e., too much mineralization for Model 1, and too little for Model 2). In this example, it would be valuable to reassess the parameterization of the crop models prior to simulating the scenarios required for the AgMIP study.

Regional information derived from expert knowledge — the "unmatched" case

There may be situations in which farm survey data are not available from which to build simulations of regional cropping systems. In this case, crop modelers will need to work with economists in the AgMIP regional team and local agronomists in the region to assemble information on the distribution of weather stations, soils, crops, and management practices that occur in the region. This situation is called the "unmatched" case, as there are not site-specific yield data against which to compare simulation results (as could be done in the example in Fig. 5).

Expert knowledge within and outside of the AgMIP regional team is drawn on to gather data on soils, sowing dates, cultivars, residue return, soil organic-matter levels, fertilization, and irrigation practices representative of the study region. The combination of cropping systems, soil, and weather occurring in the region are simulated to mimic the outputs that would come from simulations in the "matched" case. These results are compared with aggregated yield statistics of crops grown in the region over historical time-periods of 30 years to evaluate the crop models' abilities to simulate regional- or district-level yields.

Simulations to address the AgMIP core questions

With the crop models set up for crops and soils in the region (the first stage of the cropping systems modeling, Fig. 6), and the current cropping systems successfully simulated for survey farms in the regions (Stage 2, Fig. 6), simulations can be undertaken to address the three core questions in AgMIP assessments. Core Question 1 initially requires baseline simulations of the current cropping systems be undertaken with 30 years (1980–2010) of historical daily weather data. The weather data will

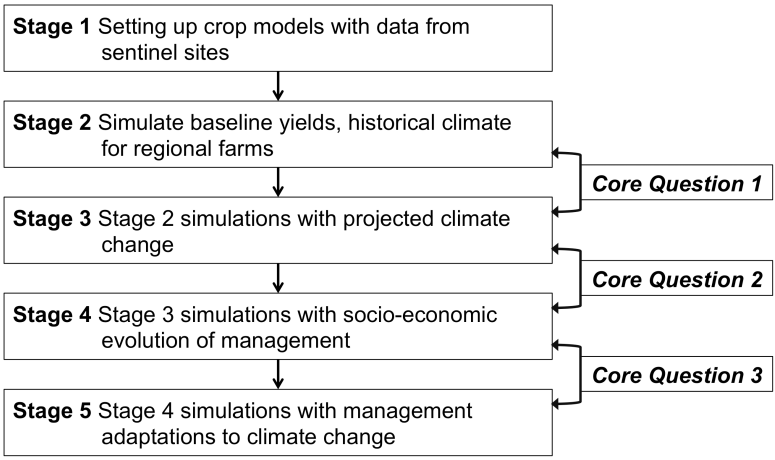


Fig. 6. Stages in the protocol for cropping-systems modeling inputs for the AgMIP regional integrated assessment.

come from the global, bias-shifted MERRA dataset, and will be a complete set of daily weather data for use in filling in missing data for observation stations (see Part 1, Chapter 3 in this volume). While the weather data will be in the generic AgMIP format, there are AgMIP IT tools (see Part 1, Chapter 6 in this volume) to re-format the data into model-specific formats for many crop models.

To address Core Question 1, yields predicted for the baseline simulations need to be compared with those predicted for a range of projected climate change scenarios (Stage 3, Fig. 6), and values of R calculated for each farm or field. For AgMIP regional integrated assessments, weather data for these simulations will have been derived from the CMIP5 GCMs with two representative concentration pathways (RCP4.5 and RCP8.5) for the near-term (2010–2039), mid-century (2040–2069), and end-of-century (2070–2099) periods using current production systems and mid-period CO_2 concentrations (see Part 1, Chapter 3 in this volume).

Outputs from the crop models are then imported into the AgMIP crop model output (ACMO) file, both as a database for the simulation results and for use as inputs to the economic analyses performed with the TOA-MD model. The IT tool ACMO can accommodate formats used in many crop models. All metadata used in the crop model simulations should also be recorded, by using the feature in ACMO to accommodate those data, and passed on to the economists. These metadata are also in the economic analyses, as are details of inputs (fertilization rate, irrigation, etc.) and other management inputs which will incur different costs.

Simulations to address Core Question 2 require specification of future crops and/or cropping systems that may have evolved under the representative agricultural

pathways (RAPs). The RAPS will consider the factors that will impact agriculture in a region, as a result of (see also Part 1, Chapter 5 in this volume):

- Predictions from global economic models about the key drivers of agricultural trends in the region (e.g., climate, shared socio-economic pathways (SSPs), and global agricultural pathways).
- Other higher-level drivers (policy, socio-economic conditions, and technology).
- The quantitative trends in the variables contained in agricultural models (crop, livestock, and economic) for the regional integrated assessment.

The output of the RAPs will be details of future cropping systems driven by global and local socio-economic changes; such as changes in fertilizer application rates caused by changes in fertilizer price, changes in the mix of crops (or other components of the agricultural system) caused by changes in economics and/or social factors, changes in varietal characteristic caused by progress in plant breeding, etc. These future cropping systems are simulated under the range of projected climate change scenarios used to address Core Question 1 and the results compared with those from the baseline simulations with projected climate (Stage 4, Fig. 6). Simulation results and metadata are output into the ACMO tool, as for Core Question 1.

There may be times when no information is available on the potential evolution of agricultural systems and their management in response to global and local socio-economic changes. In these situations, it may be possible to estimate the proportional change in production that may arise due to these technological changes, and apply this proportionality to the results from Stage 3 simulations to get the data required to address Core Question 2.

Core Question 3 is addressed through simulating the effect of adaptation strategies which are also identified through the development of the RAPs for the region. The RAPs will contain a set of technology and management adaptations to climate change that will typically include changes in the types of crops grown and the way they are managed (e.g., use of fertilizers and crop cultivars). These adaptations will be specified in the crop models (through crop management and crop cultivar specifications), and simulated under the range of projected climate change scenarios used to address Core Question 1 and the results compared with those from the baseline simulations with projected climate and management changes responding to socio-economic drivers (Stage 5, Fig. 6). As with the previous core questions, the results will be uploaded into the ACMO tool.

Example results of simulations

When we combine data from multiple farms in a region, all modeled with multiple crop models, to simulate crop production on multiple farms with a range of climate

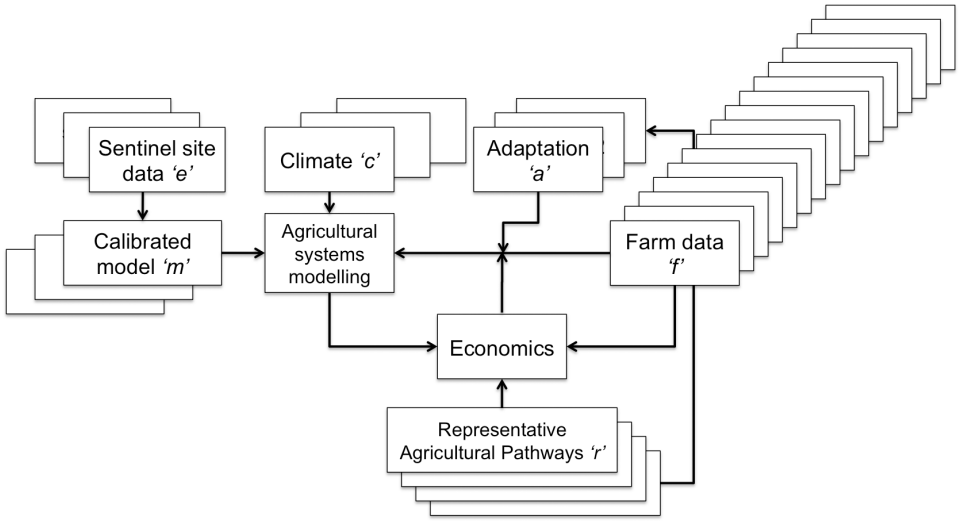


Fig. 7. Full flow diagram of the different components of an integrated climate change impact assessment in AgMIP, showing the multiple information sources for '*e*' crops (agricultural systems), '*m*' crop (agricultural) models, '*c*' climates, '*f*' farms, '*r*' representative agricultural pathways, and '*a*' climate adaptation scenarios involved in an AgMIP integrated analysis.

inputs (distributed across the region, and projected future climates) and adaptation strategies, the flow diagram shown in Fig. 1 becomes considerably more complex (Fig. 7). The result is a factorial of "*m.c.f.r.a*" simulations in the crop modeling task needed to address a regional integrated assessment. The simulation results are thus a "population" of individual simulations, and both central tendency and variance of this population are important parameters in assessing climate change impacts and adaptations. We have taken results from two of the regional case studies presented later in this volume (see Part 2, Chapters 4 and 9) to illustrate the information that can come from the cropping-systems simulations.

The two studies predict maize yields with the APSIM and DSSAT models for the years 1980–2010 for a large number of farms in the Bethlehem district in the Free State province of South Africa (Chapter 4, Part 2) and the Coimbatore district in the Tamil Nadu State of India (Chapter 9, Part 2). Maize was grown rainfed at Bethlehem, and irrigated at Coimbatore. The baseline simulations (historical climate and current management) show a wide variation in yields for Bethlehem with both models, but a narrower distribution at Coimbatore (Fig. 8), which reflects the impact of irrigation reducing the effect of climate on maize yields at the latter location. The average maize yields predicted by the two models are also substantially different at each location, with mean yields predicted from the APSIM model being lower than those from DSSAT at Bethlehem but being higher than the mean yield at Coimbatore. These

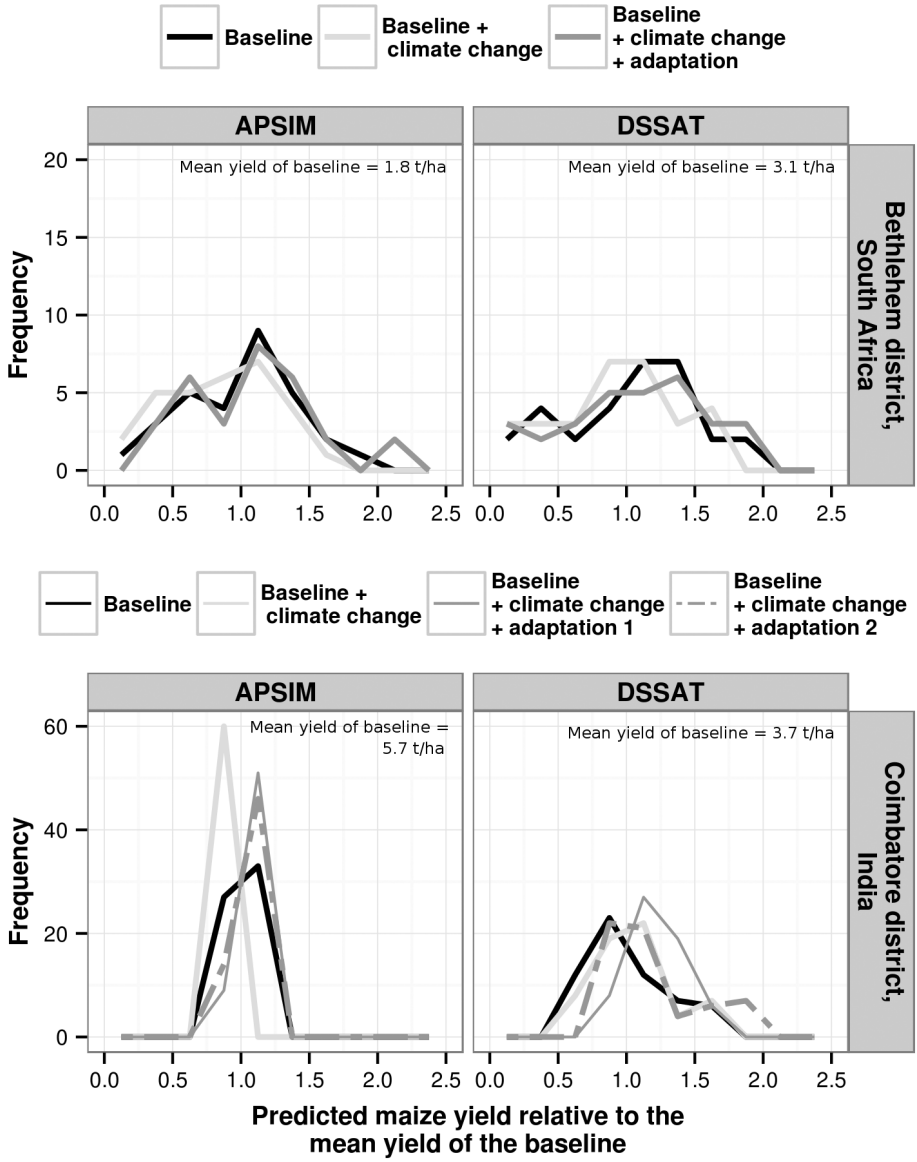


Fig. 8. Frequency distributions of relative yields of maize crop in two districts, predicted under: baseline conditions of historical climate (1980–2010) and current crop management, projected climate change (from five global climate models), and current crop management and projected climate change with management adapted to the changed climate. Yields were predicted with two models, DSSAT and APSIM. The two districts are the Bethlehem district (Free State province of South Africa) and the Coimbatore district (Tamil Nadu State, India). Maize was grown rainfed at Bethlehem, and irrigated at Coimbatore. Crop management adaptations to climate change were 30% increase in fertilizer application and use of improved long-season varieties at Bethlehem, and changed date of sowing (Adaptation 1) or increased plant population (Adaptation 2) at Coimbatore. Base data were provided by Beletse *et al.* (see Part 2, Chapter 4 in this volume) and Ponnusamy *et al.* (see Part 2, Chapter 9 in this volume) for the Bethlehem and Coimbatore districts, respectively. Results for each model are expressed relative to the mean yield predicted for the baseline condition by that model.

between-model differences provide an indication of the uncertainty in predicting maize yields in these two districts.

Despite these between-model differences in absolute yields, yields are predicted with both models to be reduced (7% to 15%) *relative* to the baseline under projected climate change at Bethlehem (Fig. 8) due to reduced rainfall and increased temperature experienced by these rainfed crops (Part 2, Chapter 4 in this volume). In contrast, at Coimbatore mean yields are predicted to decrease (by 15%) under climate change with the APSIM model but increase (by 6%) with the DSSAT model relative to the baseline. The cropping systems simulated in this district are irrigated, which reduces the effect of changed rainfall projected under climate change. Thus the different response of the two models is likely being driven by different temperature-response functions in the models.

In the study of the Bethlehem district the main adaptation to climate change was to increase in fertilizer application by 30% and use improved long-season varieties (Chapter 4, Part 2). These changes to the cropping system were predicted with both models to increase yields (by 5% to 6% relative to the baseline), which more than offsets the negative effect of climate change (Fig. 8). This increase contributed to an increase in the frequency of yields close to double the mean yield predicted by both models.

Two separate adaptations were identified in the Coimbatore district; changing the date of sowing or increasing plant population (Chapter 9, Part 2). Both adaptations were predicted to increase yields relative to the baseline with both models, with the predicted increases being greater with the DSSAT (∼18%) than the APSIM model (∼3%) relative to the baseline (Fig. 8). Date of sowing was predicted to be a somewhat beneficial adaption strategy with the DSSAT model.

These simulation results show the complexity of possible impacts of climate change. There may still be relatively high-yield farms in these districts under climate change, as well as low-yielding farms as the specific effect of climate change, and adaptation strategies adopted, will depend on the biophysical and management attributes of individual farms. The difference between the yields simulated by the two models indicates that there is uncertainty in both the impacts of, and adaptations to, climate change. The socio-economic implications of these cropping systems changes are shown in the economic analyses undertaken in the AgMIP integrated assessment (Antle *et al.*, 2014).

Discussion

The benefits of a protocol-driven approach supported by IT tools

The factorial of simulations that are undertaken in the crop modeling phase of an AgMIP integrated assessment produces a large quantity of data that have to be

analyzed and stored. Following the approach outlined above gives a reproducible methodology that will allow results from different studies to be more easily compared to provide a broader picture of the effects of climate on agriculture and food security.

Each of the arrows in Fig. 7 represents a substantial flow of data and information. Information from sentinel sites is used to parameterize and calibrate multiple crop models, which are then deployed with regional farm data and inputs on crop management and historical and projected climate to predict climate change impacts. These information flows are made more efficient and accurate by the application of the AgMIP IT tools. These tools have standardized formats that assist crop modelers in specifying outputs from simulations. Information in the databases can also be efficiently made available to other people, whether they be part of (e.g., scientists running different crop models or economists) or outside the study team. This standardization thus increases the reproducibility of regional AgMIP integrated analysis studies.

Benefits of collaboration

The activities involved in undertaking crop modeling for an AgMIP impact study have been described above in a reasonably linear fashion. However, there are many parts of such a study that require multi-disciplinary input and collaboration, and the value of this collaboration should not be overlooked. Scientists with skills in different crop models will need to collaborate to ensure crops and soils are described in the different models in a consistent manner. Crop modelers need to work with climate scientists to locate appropriate weather stations in the region. Crop modelers and economists need to interact and collaborate closely in several areas, such as the design and conduct of the farm surveys and the development of RAPs for the regions and identification of adaptation options. The AgMIP IT tools are crucial for the efficient transfer and archiving of data from the high number of simulations resulting from simulating multiple farms with multiple crop models for current and future cropping systems (arising from technology trends and adaption, driven by RAPs) all under current and future climates. These tools will help facilitate the collaboration embedded into AgMIP integrated analysis studies. The relationships developed through multi-disciplinary collaboration during conduct of an AgMIP integrated assessment may provide long-term benefits to a region.

Future challenges

The experience gained in developing and applying the protocols outlined above have revealed some challenges that need to be addressed. The most obvious of these is that the protocols only focus on crop modeling, yet we know that most

agricultural systems in the world are integrated crop–livestock systems that cannot be represented by crop modeling alone. While neither grasslands or livestock modeling has been explicitly mentioned above, the principles described in this chapter can apply to both — i.e., the "crop modeling" box in Fig. 1 becomes "agricultural-systems modeling" in Fig. 7. Information from local experiments (sentinel sites) will be required to develop and test the models in study regions, and then these models will be deployed with regional farm data and inputs on management and climate. An example of the application of AgMIP crop modeling protocols to crop–livestock intensification in Southern Africa is given in Part 2, Chapter 5 in of this volume.

Our experience has revealed some less obvious challenges. Historically, scientists (as individuals or groups) tended to have exposure to, and in-depth knowledge of, a single crop model. Given that the principles behind much soil-plant-atmosphere modeling are similar, this experience gives a modeler a general understanding of how other models work. To increase efficiency of model application it is desirable to share information between different models. So, ideally, parameters from one model can be uploaded into AgMIP databases and downloaded, reformatted, for use in another model. Our experience is that this sharing of parameter values between models is not necessarily straightforward. In hindsight, this difficulty is unsurprising. However, we now know the areas in which the overlap between models is greatest and least. In approximate decreasing order of interoperability they are:

$$\textit{Soil-water dynamics} \rightarrow \textit{Crop growth} \rightarrow \textit{Soil carbon and nitrogen cycling}.$$

Thus, parameters for a soil-water submodel in one crop model can often be *used directly*, or *converted* into appropriate parameters in another crop model; crop phenology parameters in one model may be *converted* into parameters in another model; but, except at the highest level (i.e., specifying total soil organic carbon), parameters in a soil-nitrogen submodel *provide little information* for the parameterization and initialization of another model. Within the generally positive experience of interoperability for soil-water submodels, we have found particular issues (e.g., the representation of flooded rice systems) that are represented differently enough in different models to preclude parameter sharing. AgMIP is bringing different modeling groups together to compare and thus improve their models (Asseng *et al.*, 2013; Bassu *et al.*, 2014). We anticipate this interaction will help develop a better understanding of different models across the whole agricultural modeling community, which may improve the efficiency of multi-model applications in agriculture.

Conclusions

Crop modeling is a critical part of integrated regional assessments in AgMIP. It needs to be undertaken with multiple crop models to characterize uncertainty in predictions

of production. To ensure consistency, it also needs to follow consistent protocols that specify the methods for calibrating varieties, and application of models to simulate crop yields in farms under current climate and management, and under a range of climate change and adaptation scenarios.

High-quality data are needed from experiments to calibrate the models. These experiment locations are called sentinel sites, and should include measurements of growth stages and yield, as well as information on soils, climate, and management. The calibrated models are then used to simulate crop production in farmers' fields to provide the primary yield input to the economic modeling. Information is needed on soils, management, and yields currently achieved in these fields. Three types of simulations include yields under current management with current and future climates, yields under future cropping (or agricultural) systems arising from technology trends with current and future climates, and yields under future climate with adaptation (and/or greenhouse gas mitigation) strategies.

Protocols have been defined to guide each of these steps, from what defines a sentinel site, to the information needed to interpret simulated yields and provide necessary data for economic models. The application of multiple crop models is supported by the AgMIP IT tools, which port shared information between different models and assist in the generation of management details for the farmers' fields, which can be too numerous (e.g., >100) to be practically done by hand. The successful application of the crop modeling protocols and supporting tools is clearly demonstrated by the recent results from the AgMIP regional studies (see Part 2, Chapters 1–10 in this volume).

However, a clear challenge for AgMIP is to move from analyzing cropping systems to agricultural systems, which can include the integration of crops and livestock on farms. Another challenge is further improving model interoperability, which is currently greatest for modeling soil-water dynamics, and least for soil-nitrogen dynamics. The final, largest challenge is improving the accuracy of models to simulate agricultural systems and increasing the capacity of models to represent a wider range of crop-growth resource constraints (e.g., other nutrients in addition to nitrogen) and limitations.

Acknowledgements

The authors are grateful for interactions with the teams undertaking AgMIP integrated analyses, which have shaped and clarified the crop modeling protocols described in this chapter. Special thanks go to the scientists who have shared their data to provide examples shown in this chapter, particularly Drs. Yacob Beletse, Davide Cammarano, and Sonali McDermid, Dr. Daniel Wallach for comments on the chapter and suggesting inclusion of Fig. 6, and Ms. Cecile Godde for assisting with compilation of the reference list.

References

Antle, J. M. (2011). Parsimonious multi-dimensional impact assessment, *Am. J. Agric. Econ.*, **93**, 1292–1311.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Basso, B., Gargiulo, O., Paustian, K., Porter, C. H., Robertson, G. P., Grace, P. R., and Jones, J. W. (2011). Procedures for initializing soil organic carbon pools in DSSAT-Century model for agricultural systems, *Soil Sci. Soc. Am. J.*, **75**, 69–78.

Bassu, S., Brisson, N., Durand, J. L., Boote, K., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A. R., Kersebaum, K. C., Kim, S. H., Kumar, N. S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M. V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., and Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors?, *Global Change Biol.*, **20**, 2301–2320.

Gabrielle, B., Mary, B., Roche, R., Smith, P., and Gosse, G. (2002). Simulation of carbon and nitrogen dynamics in arable soils: A comparison of approaches, *Eur. J. Agron.*, **18**, 107–120.

Hillel, D. and Rosenzweig, C. (eds.) (2012). *Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications*, Imperial College Press, London.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lisazo, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., and Tsuji, G. Y. (2010). *Decision support system for agrotechnology transfer version 4.5* [CD], Univ. of Hawaii, Honolulu, Hawaii.

Huth, N. I., Bristow, K. L., and Verburg, K. (2012). SWIM3: Model use, calibration and validation, *Trans. ASABE.*, **55**, 1303–1313.

Jones J. W., He, J., Boote, K. J., Wilkens, P., Porter, C. H., and Hu, Z. (2011). "Estimating DSSAT cropping system cultivar-specific parameters using Bayesian techniques", in Ahuja, L. R. and Ma, L. (eds.), *Methods of introducing system models into agricultural research*, SSSA book series, Madison, WI, pp. 365–393.

Kersebaum, K. C., Boote, K. J., Jorgenson, J. S., Nendel, C., Bindi, M., Frühauf, C., Gaiser, T., Hoogenboom, G., Kollas, C., Olesen, J. E., Rötter, R. P., Ruget, F., Thorburn, P. J., Trnka, M., and Wegehenkel, M. (2014). Analysis and classification of data sets for calibration and validation of agro-ecosystem models, *Environ. Model Software*, in press.

Porter, C. H., Jones, J. W., Adiku, S., Gijsman, A. J., Gargiulo, O., and Naab, J. B. (2010). Modeling organic carbon and carbon mediated soil processes in DSSAT v4.5., *Operational Res.,* **10**, 247–278.

Rötter, R. P., Carter, T. R., Olesen, J. E., and Porter, J. R. (2011). Crop-climate models need an overhaul, *Nat. Clim. Change*, **1**, 175–177.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Antle, J., Nelson, G., Porter, C., Janssen, S., Asseng, S., Winter, J. M., and Greeley, A. P. (2013). The agricultural model intercomparison and improvement project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Thorburn, P. J., Meier, E. A., and Probert, M. E. (2005). Modelling nitrogen dynamics in sugarcane systems: Recent advances and applications, *Field Crop Res.*, **92**, 337–352.

Thorburn, P. J., Biggs, J. S., Attard, S. J., and Kemei, J. (2011). Environmental impacts of irrigated sugarcane production: Nitrogen lost through runoff and leaching, *Agric. Ecosys. Environ*., **144**, 1–12.

This page intentionally left blank

Chapter 5

Representative Agricultural Pathways and Scenarios for Regional Integrated Assessment of Climate Change Impacts, Vulnerability, and Adaptation

Roberto O. Valdivia[1], John M. Antle[1], Cynthia Rosenzweig[2], Alexander C. Ruane[2], Joost Vervoort[3], Muhammad Ashfaq[4], Ibrahima Hathie[5], Sabine Homann-Kee Tui[6], Richard Mulwa[7], Charles Nhemachena[8], Paramasivam Ponnusamy[9], Herath Rasnayaka[10], and Harbir Singh[11]

[1]*Oregon State University, Corvallis, OR, USA*

[2]*NASA Goddard Institute for Space Studies, New York, NY, USA*

[3]*University of Oxford, Oxford, UK*

[4]*University of Faisalabad, Faisalabad, Pakistan*

[5]*Prospective Agricole et Rurale, Dakar-Fann, Senegal*

[6]*International Crops Research Institute for the Semi-Arid Tropics, Bulawayo, Zimbabwe*

[7]*University of Nairobi, Nairobi, Kenya*

[8]*Human Sciences Research Council, Pretoria, South Africa*

[9]*Tamil Nadu Agricultural University, Coimbatore, India*

[10]*Department of Agriculture, Peradeniya, Sri Lanka*

[11]*Indian Council of Agricultural Research, Modipuram, India*

This page intentionally left blank

Introduction

The global change research community has recognized that new pathway and scenario concepts are needed to implement impact and vulnerability assessment where precise prediction is not possible, and also that these scenarios need to be logically consistent across local, regional, and global scales (Moss *et al.*, 2008, 2010). For global climate models, representative concentration pathways (RCPs) have been developed that provide a range of time-series of atmospheric greenhouse-gas concentrations into the future (Moss *et al.*, 2008, 2010; van Vuuren *et al.*, 2012a). For impact and vulnerability assessment, new socio-economic pathway and scenario concepts have also been developed (Kriegler, 2012; van Vuuren *et al.*, 2012b), with leadership from the Integrated Assessment Modeling Consortium (IAMC).

> The new scenarios will provide quantitative and qualitative narrative descriptions of socioeconomic reference conditions that underlie challenges to mitigation and adaptation, and combine those with projections of future emissions and climate change, and with mitigation and adaptation policies. They will provide a framework for underpinning, creating, and comparing sectoral and regional narratives.
>
> (Carter *et al.*, 2012).

This chapter presents concepts and methods for development of regional representative agricultural pathways (RAPs) and scenarios that can be used for agricultural model intercomparison, improvement, and impact assessment in a manner consistent with the new global pathways and scenarios.[1] The development of agriculture-specific pathways and scenarios is motivated by the need for a protocol-based approach to climate impact, vulnerability, and adaptation assessment. Until now, the various global and regional models used for agricultural-impact assessment have been implemented with individualized scenarios using various data and model structures, often without transparent documentation, public availability, and consistency across disciplines. These practices have reduced the credibility of assessments, and also hampered the advancement of the science through model intercomparison, improvement, and synthesis of model results across studies (see, e.g., Easterling *et al.*, 2007; Nelson *et al.*, 2014; Rosenzweig *et al.*, 2013a). The recognition of the need for better coordination among the agricultural modeling community, including the development of standard reference scenarios with adequate agriculture-specific detail, led to the creation of the Agricultural Model Intercomparison and Improvement Project (AgMIP) in 2010. The development of RAPs is one of the "cross-cutting themes" in AgMIP's work plan, and has been the subject of ongoing work by AgMIP since its creation (Antle *et al.*, 2014b; Rosenzweig *et al.*, 2013b).

[1] In the following section we provide definitions that clarify the difference between pathways and scenarios as we use them in this chapter.

The first section of this chapter presents the concepts underlying AgMIP's development of RAPs at global, regional, and local scales. The second section provides a detailed description of the methods used to develop regional RAPs by the AgMIP regional teams. The third section presents a summary of the regional teams' RAPs and their implications for climate impact assessment and adaptation, then discusses lessons learned from the experiences of the regional teams in implementing the RAP development process. The final section summarizes and draws implications for future regional RAPs development and use.

Box 1. Acronyms.

AgMIP	Agricultural Model Intercomparison and Improvement Project
BAU	Business-as-usual
CCAFS	Climate Change, Agriculture and Food Security Research Program of the CGIAR
CGIAR	Consultative Group on International Agricultural Research
CMIP	Coupled Model Intercomparison Project
CSM	Cropping system model
ESM	Earth system model
GCM	Global climate model
GDP	Gross domestic product
IAM	Integrated assessment model
IAMC	Integrated Assessment Modeling Consortium
RCM	Regional climate model
RCP	Representative concentration pathway
SAS	Story and simulation approach to scenario analysis
SRES	Special Report on Emissions Scenarios
SSP	Shared socio-economic pathway
TOA-MD	Tradeoff Analysis Model for Multi-dimensional Impact Assessment
RAP	Representative agricultural pathway

The Conceptual Framework for RAP Development

In this section we first describe briefly the new global pathway and scenario concepts that have been developed for use with global integrated assessment models. Then we present AgMIP's global and regional integrated assessment framework and discuss the central role that RAPs play in it. Finally, we summarize some of the conceptual issues that arise in constructing sector-specific and region-specific pathways that link to global pathways.

Pathway architecture: Representative concentration pathways (RCPs) and shared socio-economic pathways (SSPs)

The parallel development of new greenhouse gas concentration and socio-economic pathways is intended to ameliorate inconsistencies at the aggregate, global scale. Figure 1 presents a scenario matrix showing how RCPs and SSPs proposed by Kriegler *et al.* (2012) could be combined. As this matrix implies, RCPs and SSPs are designed to be independent dimensions, to reflect the fact that a particular concentration's trajectory could correspond to various socio-economic conditions that cause and are caused by greenhouse-gas emissions and the resulting climate change. Thus, various socio-economic scenarios could be designed to represent, say, future worlds with either low or high emissions combined with various levels of economic activity and types of mitigation and adaptation capabilities and policies. As Fig. 1 also indicates by the shading, some combinations of RCPs and SSPs may not be plausible (say, very low emissions with very high economic growth).

Socio-economic pathways are multi-dimensional concepts that embody economic and social development, adaptation and mitigation capability, and non-climate policy dimensions. To incorporate climate policy dimensions, researchers have proposed "Shared Climate Policy Assumptions" as another set of dimensions of an impact assessment (Kriegler *et al.*, 2014). As with the Special Report on Emissions Scenarios (SRES) scenarios (Nakicenovic *et al.*, 2000), a key feature of SSPs is a set of corresponding narratives that contain the rationale for the features of the pathway. Researchers can use these narratives to interpret the pathway logic; a feature

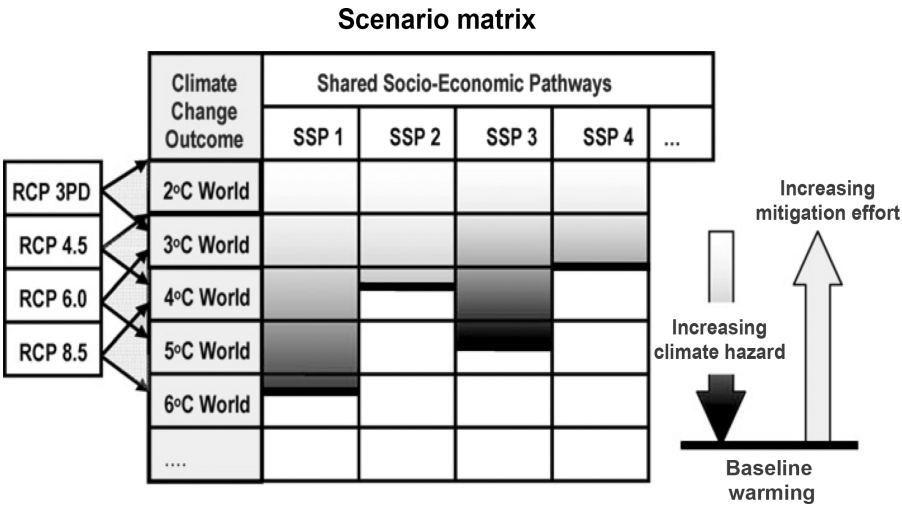


Fig. 1. Scenario matrix with SSPs on the horizontal axis and RCPs on the vertical axis (Kriegler *et al.*, 2012). Note that the SSPs listed here are hypothetical and therefore do not correspond with those in Fig. 2. Reprinted from Kregler *et al.* (2012) with permission from Elsevier.

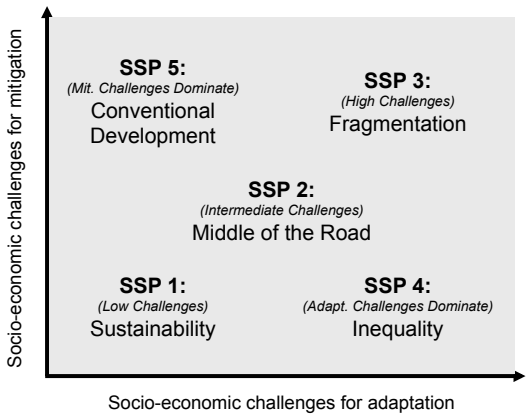


Fig. 2. Five-pathway SSP matrix (O'Neill *et al.*, 2012).

important for the "sharing" or using the pathways for different types of research, and also for developing sector- and region-specific versions such as the agricultural pathways we discuss in the next section.

For communication with the research community and stakeholders, it is useful to be able to represent these multi-dimensional concepts in a two-dimensional form. Figure 2 shows an SSP matrix that defines five possible SSPs in terms of different degrees of "challenges to adaptation" (or ability to deal with climate change that has already occurred) and "challenges to mitigation" (or ability to restrain the extent to which climate change will occur) as well as other features of socio-economic development. These five SSPs have become the basis for quantification of key drivers, such as population, economic growth, urbanization, education, and land use (International Institute for Applied Systems Analysis, 2012). Narratives associated with these SSPs can be found in O'Neill *et al.* (2012).

Two key features of the new global pathway developments should be emphasized. First, it is assumed that socio-economic pathways can be defined in a way that is largely independent of the emissions pathway and associated changes in climate that occur — this is the logical basis for the "matrix architecture" of the RCPs and SSPs presented in Fig. 1. Second, the characterization of SSPs is fundamentally "climate-centric" by being defined in relation to climate adaptation and mitigation challenges.

The role of RAPs in AgMIP's global and regional integrated assessment framework

Building on AgMIP's integrated assessment framework (Rosenzweig *et al.*, 2013b), Fig. 3 provides a stylized representation of the linkages between global climate

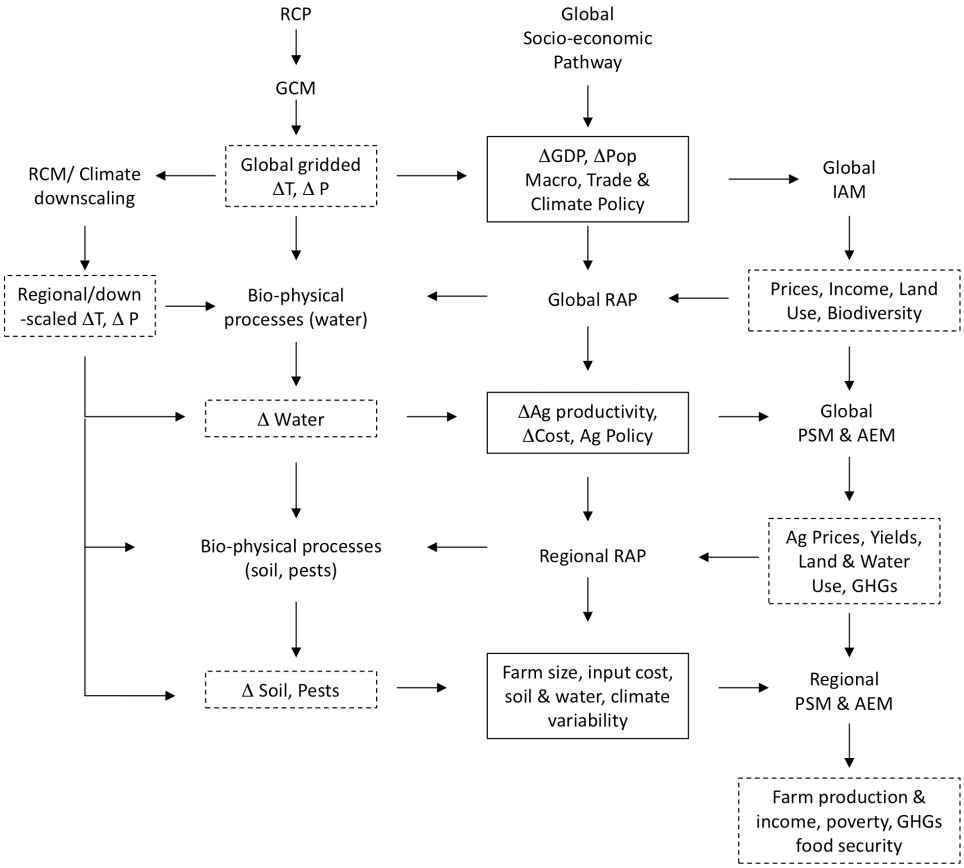


Fig. 3. An elaboration of AgMIP's global and regional integrated assessment modeling framework. Note: RCP = representative concentration pathway; GCM = global climate model; RCM = regional climate model; T = temperature, P = precipitation; IAM = integrated assessment model; RAP = representative agricultural pathway; PSM = biophysical production system model; AEM = agricultural economic model; solid boxes indicate variables determined by global socio-economic pathways and RAPs, dashed boxes indicate model outputs. Moving from top to bottom represents different geographic scales (global to regional to local), and the three columns of the figure represent biophysical models and data (left-hand column), biophysical and socio-economic pathways (center), and impact models (right-hand column).

models and data, global integrated assessment models (IAMs), and global and regional agricultural models used for climate impact, adaptation, mitigation, and vulnerability assessment. This figure shows the hierarchical structure of the relationships between global and regional data and models, and between aggregate and disaggregate ("regional") data and models. Dashed boxes represent model outputs at each level, which serve as inputs for lower-level (sectoral or regional) models. However, these higher-level outputs are not sufficient to implement the

lower-level models, so they are augmented by variables derived from pathways developed for each level of analysis. Moving from top to bottom, Fig. 3 represents different geographic scales (global to regional to local), and the three columns of the figure represent biophysical models and data (left-hand column), biophysical and socio-economic pathways (center), and impact models (right-hand column).

The top of the figure represents the main components of global integrated assessments. RCPs and GCMs combine to generate climate outputs on a global gridded basis. These climate outputs are combined with inputs from global socio-economic pathways, such as projected rates of economic growth and population, macroeconomic and trade policy parameters, and climate policy assumptions, which serve as inputs into global IAMs. These global IAMs typically generate global and multi-country or country economic outcomes such as production, prices, and incomes; some models also simulate certain biological or physical outcomes such as changes in land use or land cover. Depending on the type of model, these outcomes may be generated for multi-country regions, by country, or subregions of a country.

Agricultural assessment models operate at both global and regional scales. At the global level, biophysical production system models can be simulated on a gridded basis (Havlík *et al.*, 2014; Rosenzweig *et al.*, 2013a) or on a point basis and then aggregated (Ewert *et al.*, 2011). In some cases, these models are used to generate inputs for partial- or general-equilibrium agricultural economic models (Nelson *et al.*, 2010, 2014). These models may use outputs from the global IAMs (e.g., prices of energy, income), or may use some of the same drivers from the global socio-economic pathways that global IAMs use, such as gross domestic product (GDP) and population growth rates. However, both agricultural production system models (PSMs; including crop and livestock simulation models) and agricultural economic models (AEMs), require additional inputs that are not provided by global IAMs. These variables include technology or productivity growth rates for individual outputs (crops, livestock); and, in more detail, food-specific demand elasticities; and agriculture-specific inputs as labor, machinery, seed, fertilizers, irrigation water, and fuels. In addition, agriculture-specific policy parameters may be needed, e.g., for domestic output or input taxes or subsidies, and parameters for trade policy (e.g., tariffs). Thus, global RAPs are needed that are consistent with global socio-economic pathways but that provide the additional sector-specific detail needed to implement biophysical PSMs and AEMs.

The biophysical component of the assessment framework beyond the GCM outputs involves several components. First, regional climate models or downscaling of gridded GCM outputs to higher spatial and temporal resolution is needed to serve as inputs to global gridded PSMs and regional gridded or point-based PSMs.

In addition, the framework may include a water component (e.g., the SWAT (Soil and Water Assessment Tool) model), or a soil erosion component (e.g., using the EPIC (Erosion Productivity Impact Calculator) model). These models may be implemented on a global basis, as is done for water supply-demand in the IMPACT AEM model (Rosegrant *et al.*, 2012), or may be done on a gridded basis as is done with EPIC in the GLOBIOM AEM model (Havlík *et al.*, 2011). Similar model linkages may be done on a national or subnational model, as with FASOM (Forest and Agricultural Sector Optimization Model) for the US (Ohrel *et al.*, 2010) or the TOA-ME (Tradeoff Analysis Model for Multi-dimensional Market Equilibrium) model (Valdivia *et al.*, 2012). At both the global and regional scales, these models may involve drivers such as details of land use or water use that are not available from higher-level models, and thus need to be specified as part of RAPs.

Global AEMs generate projections of globally consistent market equilibrium commodity-specific prices, yields, and acreages that can be used as drivers for regional AEMs which do not solve for global equilibria. There are various types of regional AEMs, ranging from representative farm optimization models, regional optimization models (e.g., Merel and Howitt 2014), regional technology adoption and impact assessment models such as TOA-MD (Antle 2011; Antle and Valdivia, 2011; Antle *et al.*, 2014a), regional land-use models (Wu *et al.*, 2004), and national partial-equilibrium economic models such as FASOM (Ohrel *et al.*, 2010) or the SEAMLESS-IF system developed for the EU region (van Ittersum *et al.*, 2008). These models may utilize variables from global models as drivers, notably, prices, productivity, and land use.

At the regional level, some AEMs continue to be formulated on a commodity basis, but some models represent production of crops and livestock as integrated systems. Some models also incorporate a household production component, as well as non-agricultural income-generating activities. Generally, models do not exist to project this level of detail for model inputs and thus inputs must be addressed using RAPs. Essential details typically include input cost or use by type of production activity, including livestock; some models also require data on farm and household characteristics such as farm size and number of people in the household, as well as non-agricultural income. Some models require detailed use on farm labor, including household members and hired workers. Greater detail on policy parameters, such as domestic output, input, and environmental subsidies may be needed, as well as parameters related to climate mitigation policy. When these models are linked to PSMs, details on management inputs are also required for those models.

A major limitation of most PSMs is that they are not capable of simulating the effects of pests and diseases on crops or livestock. Therefore, an important topic for transdisciplinary collaboration is to address the potential of new pests and diseases

to impact the production system being modeled, and how these pests and diseases may be managed. In the meantime, pest and diseases can be addressed using RAPs.

Implications for RAP design

The framework in Fig. 3 has a number of important implications for the design of RAPs (Antle *et al.*, 2014b).

Is the matrix architecture useful for RAPs?

The integrated assessment framework presented above raises questions about the usefulness of the "matrix" architecture proposed for the development of RCPs and SSPs at the global scale. As Fig. 3 implies, the issues of spatial and temporal scale, and associated issues of aggregation and disaggregation, must be addressed when pathways and scenarios are linked across scales. The effect of this linkage across scales is to blur the distinction between "drivers" and "outcomes" that underlies the pathway concept. For example, consider the role that prices play on the global, regional, and local scales. The price of a commodity like wheat is determined by global markets, and thus is an outcome of global models, whereas it plays the role of an input or driver on the regional or local scale. Thus, because the global models determine prices as functions of specific RCPs and SSPs, if prices are considered to be part of a RAP then the RAP cannot be independent of the RCP or SSP. Similar issues arise with policies, e.g., climate mitigation policy, which would be expected to interact dynamically with emissions and thus with the rate of climate change. Likewise, elements of RAPs could include biological processes such as the spread of pests and diseases that are determined in part by climate.

A response to this criticism could be that RAPs are meant to be elements of the future world that can be defined independently of climate, and that climate-specific elements should be part of "scenarios" that are based on a RAP, and which potentially include adaptation packages designed to respond to specific climate change projections while still being consistent with the broader pathway. However, if the many key features of the future world are climate-related, then one can question how useful it is to define "pathways" separately from "scenarios". As Fig. 1 shows, the farther down ones goes from global to regional and local scale, the more climate-dependent elements there are likely to be in an analysis, and thus the less useful is the matrix architecture.

Should RAPs be climate-centric?

Agricultural-impact models depend strongly on both biophysical and socio-economic drivers, and historically agriculture has undergone rapid technological

change that has induced large changes in the economic organization of the agricultural sector. As a result, previous studies have consistently shown that trends in non-climate factors, such as population growth and technological change, are likely to have a large influence on agricultural production and related human well-being (Nelson *et al.*, 2010; Parry *et al.*, 2004). Accordingly, the framework proposed by Antle *et al.* (2014b) for the development of RAPs (elaborated below) is based on the characterization of key biophysical and socio-economic drivers. This approach contrasts with the climate-centric global pathway and scenario framework described above that emphasizes "challenges to adaptation" and "challenges to mitigation" as key dimensions that guide global pathway development for use in global IAMs.

Transdisciplinary pathways: Combining biophysical and socio-economic dimensions

One of the key motivations for the new pathways concepts has been the growing recognition of a need for a more integrative or parallel process to develop projections of emissions and socio-economic development. AgMIP's experience in developing RAPs shows that this process must be not only parallel but *trans-disciplinary*, which means that it needs to involve an integrative process of collaboration among disciplines to produce outcomes that transcend what can be achieved by individual disciplines, or by simple passing of data or other information from one disciplinary researcher or group to another.

The need for a transdisciplinary approach is motivated, firstly, by the fact that agricultural pathways need to address key biophysical dimensions important to agriculture, as discussed above. Moreover, a transdisciplinary approach is needed to ensure logical consistency between model components on a given spatial and temporal scale, as well as across scales (see Fig. 4). As the discussion of Fig. 3 showed, this need for a trans-disciplinary approach increases as we move from the highly aggregated level at which global pathways and scenarios are developed and used in models, to the disaggregated sectoral, regional, and local levels at which analysis of climate impact and adaptation also needs to be carried out.

Figure 5 portrays five possible RAPs corresponding to combinations of low and high economic development and more or less sustainable biophysical conditions. In contrast to Figs. 1 and 2, the axes are defined in positive terms. RAP 1 is the case of adverse synergies resulting in low outcomes in both dimensions, which might occur if persistently high population growth led to both poverty and environmental degradation as is true in some counties today. RAP 3 is described as the opposite case of win–win synergies in both dimensions and thus represents sustainable high growth, e.g., a shift to soil- and water-conserving tillage systems that also achieve high

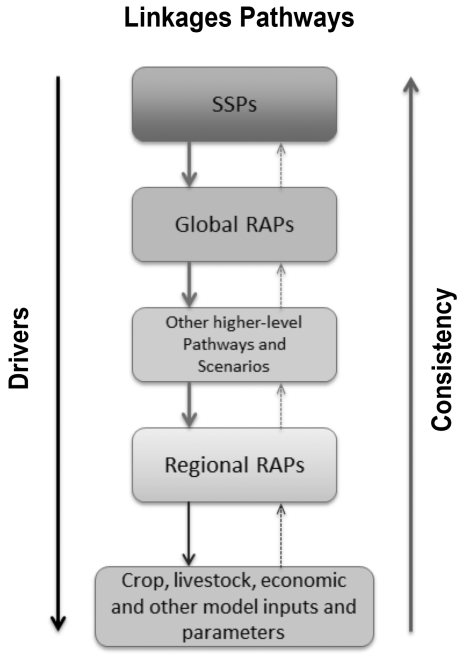


Fig. 4. Linkages from global and regional pathways and scenarios for disaggregation (downscaling) and development of model-specific scenarios.

productivity. RAPs 4 and 5 represent cases of strong tradeoffs between economic and environmental outcomes. RAP 4 could correspond to a case of policies that achieve environmental protection by severely restricting economic activity; RAP 5 might correspond to the continuation of present trends in some industrialized countries where productivity growth continues at a high level by continuing to exploit natural resources in an unsustainable manner. This latter example illustrates that the time-horizon of a RAP is a crucial element, since RAP 5 might be a plausible option in the near term but not feasible in the longer run if the high rate of economic growth depends on an unsustainable rate of depletion of natural resources such as soil, water, or biodiversity. RAP 2 represents a middle-ground balance of economic and sustainability indicators.

As we noted above, a basic question about this type of RAP design is whether they can be defined independently of greenhouse-gas concentration scenarios (RCPs). In our view, this may be a useful way to think about global RAPs, although even at this level, defining elements such as water resources independently of climate scenarios seems questionable unless it is clearly defined as only the demand element of a more complex water-resource-management system. As the research focus moves to regional and local scales, we find that this decoupling is less useful.

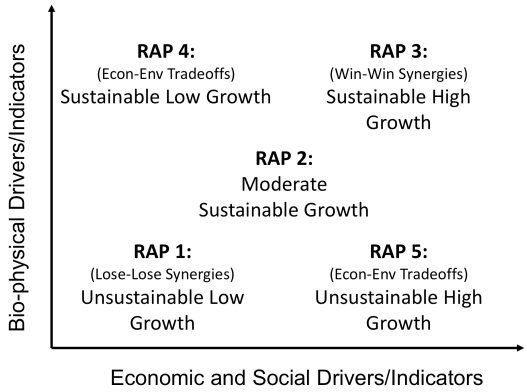


Fig. 5. Five-pathway "synergies and tradeoffs" matrix with pathway descriptions (Antle *et al.*, 2014b).

Why "representative" agricultural pathways and scenarios?

Some of the developers of new socio-economic pathways felt it was important to designate them as "shared" rather than "representative" because they are designed to be multi-dimensional and thus are not easily confined to a single or a small number of variables (in contrast to RCPs, which operate on one dimension; greenhouse-gas emissions) (Kriegler *et al.*, 2012). There is also the hope that many socio-economic pathways might be created so that researchers can select from a "menu" of alternatives. Additionally, some scenario researchers think that there is a tendency to develop future scenarios that are too much like the present, and fail to consider possible "surprises" or possibly unlikely but potentially important alternative futures (van Notten *et al.*, 2005). While these are important considerations, we take the view here that there are also good reasons to propose the development of "representative" socio-economic pathways and more specific RAPs. Two critical, practical issues lead us to this approach; we refer to these issues as the aggregation and dimensionality problems.

Aggregation

Global climate models project climate outcomes that are typically aggregated spatially and temporally (e.g., monthly data for 150-km grid cells). Aggregate economic models are based on data that are aggregated across large numbers of producers and consumers. After these models are simulated, data are typically "downscaled" or disaggregated to smaller grid cells or other spatial units. Similarly, construction of socio-economic pathways and scenarios requires some form of spatial "downscaling" or disaggregation of global trends to subglobal regions, typically to national scales, and then further to subnational regions for impact, adaptation, and

vulnerability analysis. This problem was recognized in early climate impact assessment work, and "linear" methods were used that were based on the assumption that all units in a region followed trajectories in proportion to the aggregate value (Gaffin *et al.*, 2004). We observe that the need for "downscaling" is driven by the use of aggregated data and models, and thus we might better describe the problem as one of "disaggregation".

As noted by O'Neill *et al.* (2012), there is a need for a process by which more flexible and meaningful disaggregation can be implemented to create global pathways and scenarios. For example, the first set of SSPs developed by the IAMC contain global population and GDP growth rates as well as national growth rates (International Institute for Applied Systems Analysis, 2012). Linking global pathways to subglobal (say, national) pathways is a way to meaningfully disaggregate so that the subglobal variables are consistent with plausible local storylines, and are not arbitrary values from mechanistic downscaling rules (Zurek and Henrichs, 2007).

Dimensionality

However aggregation and disaggregation are done, one goal of scenario analysis is to understand the sensitivity of results to scenario assumptions, which implies the use of multiple scenarios. Even if this is for a small number of alternative regional pathways for each major global trend, given the number of regions in the world there will be a large number of possible combinations of all trajectories (for example, the current attempts to establish population and GDP trajectories for SSPs are developing national data). Additionally, when we consider that there are multiple RCPs and many climate models, the number of different scenarios to be considered is large. If in addition, an ensemble approach is taken to the IAMs, the number becomes larger yet. When we then consider multiple regional pathways, and multiple subregions, adaptation scenarios, mitigation, and other policy scenarios, the dimensionality rapidly multiplies.

Inevitably, it will be a practical necessity to develop a small number of pathways for shared use as reference scenarios and for standards of intercomparison, model improvement, and impact assessment. This was the original motivation of the RCPs used in GCM simulations, as specific pathways were chosen to represent a family of equally plausible pathways with similar outcomes in order to reduce dimensionality and introduce a standard. Individual teams can design and use as many pathways and scenarios as they wish, but our view is that the "standard" ones will inevitably become the ones that are considered to be representative of major plausible development pathways, much as a subset of the SRES and RCPs have been widely used. We note that research teams can develop other pathway concepts that may be considered "wildcards" or "outliers" to test how climate impacts or adaptation may play out

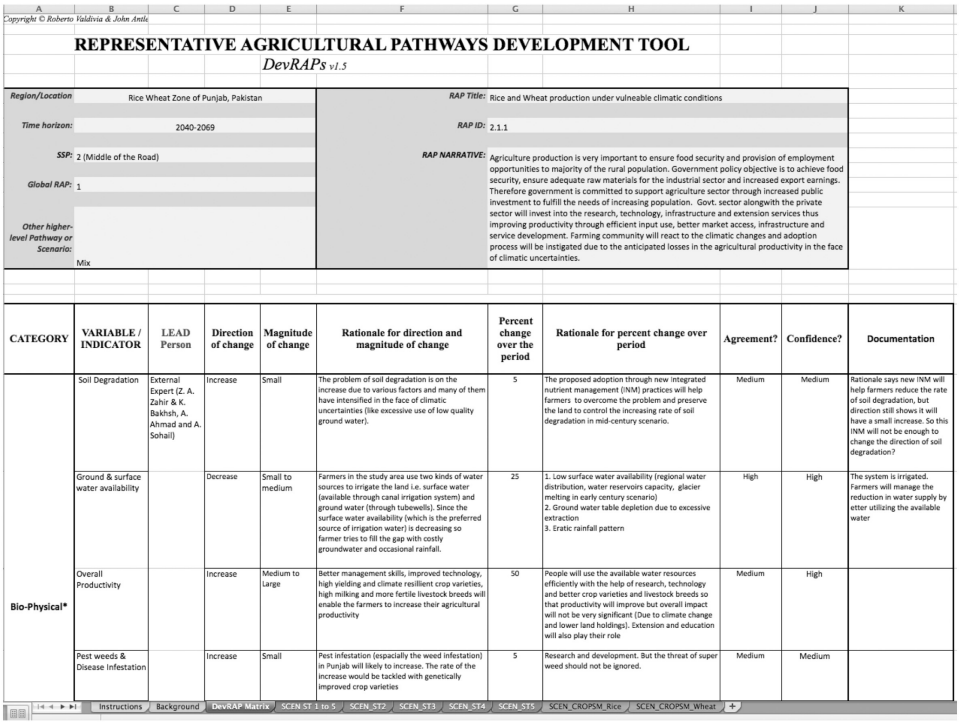
under, e.g., more extreme conditions, but we expect that these outlier pathways will be less widely used by large numbers of research teams, and will not be considered useful reference pathways.

We suspect that if many different pathways are developed, researchers will find that many of them do not result in substantially different implications for impact assessment or adaptation analysis. Thus, what we would see as most useful is a small number of pathways that represent substantially different outcomes for key socio-economic variables. For example, one can imagine a world in which real agricultural commodity prices (prices adjusted for inflation) continue the downward trends observed during the 20th century; and one can also imagine that the world is currently at a turning point (as evidenced by recent spikes and volatility in food prices), and that real agricultural commodity prices will be on an upward trend during the 21st century. Indeed, some global agricultural models predict decreases and some predict increases (Nelson *et al.*, 2014).

Designing Regional RAPs

RAPs must be designed to be part of a logically consistent set of drivers and outcomes from global to regional and local, as illustrated in Figs. 3 and 4. To create pathways and corresponding scenarios at global, regional, or local scales, teams of scientists and other experts with knowledge of the agricultural systems and regions work together through a step-wise process similar to the "Story and Scenario" approach (Alcamo, 2008). AgMIP's experience with the implementation of RAPs has shown that it is a fundamentally *transdisciplinary process* that brings together the various elements of a research team. As Fig. 3 shows, the RAPs are a central element of the research design, and as a result, the RAP development process facilitates the overall design and also improves the communication among the research team that is essential to implement the regional integrated assessment methodology described in Part 1, Chapter 2 in this volume. Another key element of the RAP process is that it brings stakeholders into the research design process at an early stage. This close linkage to stakeholders helps to ensure the legitimacy, credibility, and salience of RAPs to users; key traits of scenarios used in multi-stakeholder environments (Cash *et al.*, 2003).

Valdivia and Antle (2012) have developed an Excel spreadsheet tool called DevRAP (in Beta version) to facilitate this process (Fig. 6). DevRAP provides a structure to guide this process and to record and document the information systematically, and then use it to develop model-specific quantitative scenarios. For example, a version has been designed to provide a structured format for the parameters of the TOA-MD model (Antle and Valdivia, 2011) and crop simulation models; the DevRAP tool can be modified easily to fit other biophysical and economic models.



Copyright © Roberto Valdivia & John Antle

REPRESENTATIVE AGRICULTURAL PATHWAYS DEVELOPMENT TOOL

DevRAPs v1.5

Region/Location	Rice Wheat Zone of Punjab, Pakistan	*RAP Title:*	Rice and Wheat production under vulneable climatic conditions
Time horizon:	2040-2069	*RAP ID:*	2.1.1
SSP:	2 (Middle of the Road)	*RAP NARRATIVE:*	Agriculture production is very important to ensure food security and provision of employment opportunities to majority of the rural population. Government policy objective is to achieve food security, ensure adequate raw materials for the industrial sector and increased export earnings. Therefore government is committed to support agriculture sector through increased public investment to fulfill the needs of increasing population. Govt. sector alongwith the private sector will invest into the research, technology, infrastructure and extension services thus improving productivity through efficient input use, better market access, infrastructure and service development. Farming community will react to the climatic changes and adoption process will be instigated due to the anticipated losses in the agricultural productivity in the face of climatic uncertainties.
Global RAP:	1		
Other higher-level Pathway or Scenario:	Mix		

CATEGORY	VARIABLE / INDICATOR	LEAD Person	Direction of change	Magnitude of change	Rationale for direction and magnitude of change	Percent change over the period	Rationale for percent change over period	Agreement?	Confidence?	Documentation
Bio-Physical*	Soil Degradation	External Expert (Z. A. Zahir & K. Bakhsh, A. Ahmad and A. Sohail)	Increase	Small	The problem of soil degradation is on the increase due to various factors and many of them have intensified in the face of climatic uncertainties (like excessive use of low quality ground water).	5	The proposed adoption through new Integrated nutrient management (INM) practices will help farmers to overcome the problem and preserve the land to control the increasing rate of soil degradation in mid-century scenario.	Medium	Medium	Rationale says new INM will help farmers reduce the rate of soil degradation, but direction still shows it will have a small increase. So this INM will not be enough to change the direction of soil degradation?
	Ground & surface water availability		Decrease	Small to medium	Farmers in the study area use two kinds of water sources to irrigate the land i.e. surface water (available through canal irrigation system) and ground water (through tubewells). Since the surface water availability (which is the preferred source of irrigation water) is decreasing so farmer tries to fill the gap with costly groundwater and occasional rainfall.	25	1. Low surface water availability (regional water distribution, water reservoirs capacity, glacier melting in early century scenario) 2. Ground water table depletion due to excessive extraction 3. Eratic rainfall pattern	High	High	The system is irrigated. Farmers will manage the reduction in water supply by etter utilizing the available water
	Overall Productivity		Increase	Medium to Large	Better management skills, improved technology, high yielding and climate resilient crop varieties, high milking and more fertile livestock breeds will enable the farmers to increase their agricultural productivity	50	People will use the available water resources efficiently with the help of research, technology and better crop varieties and livestock breeds so that productivity will improve but overall impact will not be very significant (Due to climate change and lower land holdings). Extension and education will also play their role	Medium	High	
	Pest weeds & Disease Infestation		Increase	Small	Pest infestation (espacially the weed infestation) in Punjab will likely to increase. The rate of the increase would be tackled with genetically improved crop varieties	5	Research and development. But the threat of super weed should not be ignored.	Medium	Medium	

Instructions | Background | DevRAP Matrix | SCEN_ST 1 to 5 | SCEN_ST2 | SCEN_ST3 | SCEN_ST4 | SCEN_ST5 | SCEN_CROPSM_Rice | SCEN_CROPSM_Wheat

Fig. 6. Example of the RAP matrix in the DevRAP Tool (Antle and Valdivia, 2012), with example for the rice–wheat zone of Punjab, Pakistan. Developed by AgMIP Pakistan regional research team (see Part 2, Chapter 7 in this volume).

To implement RAPs following the matrix in Fig. 6, the team defines a general narrative of the RAPs, identifies socio-economic indicators and develops narratives and quantitative information for them, incorporating appropriate expertise from within the team and also recruiting outside expertise as feasible. Using that format, the team can follow a series of steps for RAPs development:

1. *Define time-period for analysis*: For example, AgMIP has designated three "time-slices" in the 21st century for analysis: early-century (2010–2039), mid-century (2040–2069), and late-century (2070–2099).
2. *Select higher-level pathways*: Following the concept of a nested approach, relevant narratives and quantitative information from selected higher-level pathways (e.g. SSPs, global RAPs) need to be extracted.
3. *Identify variables from higher-level pathways and models*: Selected output variables from higher-level models (e.g., prices, productivity trends, and land-use-change data from global models) can be used as drivers or inputs for a regional model.

4. *RAP research process*:

   a. First meeting:

      i. Start with a "business-as-usual" (BAU) RAP.
      ii Team members identify key parameters that will likely be affected by higher-level pathways and draft RAP narrative.
      iii. Team members are assigned variables for research.
      iv. Team members conduct research — use of templates for reporting and supporting documentation. These templates can be distributed to experts for feedback.

   b. Second meeting:

      i. Team members report findings and discuss storylines for each variable.
      ii. BAU RAP is finalized using the DevRAP tool and complete the following information:

         1. Complete information for each parameter:
         2. Direction, magnitude, and rate of change.
         3. Narrative logic for changes.
         4. Check for internal consistency with higher-level pathways and models' variables.
         5. Ascertain level of agreement among participants.
         6. If level of agreement is low, repeat process until acceptable levels are achieved.
         7. Assess whether one or more parameters need to be revised by other experts or selected for sensitivity analysis.
         8. Document source of information (pathway, model, literature, expert).

      iii. Additional RAPs are identified.
      iv. Process similar to BAU is carried out with additional background research.

   c. Meeting(s) to create additional RAPs — follow similar steps as in a and b.
   d. RAPs distributed to stakeholders and outside experts.

5. *Modelers develop scenarios*: The modeling team utilizes the pathway variables, along with other data, to set model parameters. For each pathway, multiple scenarios are possible, e.g., the modeling team can design a sensitivity analysis by varying parameters over a range consistent with a RAP, or in the context of assessing impacts of climate change, multiple scenarios can be developed to test different adaptation strategies.

RAPs and scenario documentation to address the reproducibility and conversion problems

Two key problems in the story and simulation approach to scenario analysis (SAS; Alcamo, 2008) are caused by the element of subjective judgment needed by a group to translate RAPs into specific model scenarios. There is a one-to-many relation: By design, many different scenarios are consistent with a RAP. The DevRAP tool was developed as a way to address this problem, by structuring and documenting the RAP information and how it is translated into scenarios (model parameters). The DevRAP tool also should address the "conversion problem" in scenario analysis, i.e., how qualitative and more general information in a RAP is translated into specific values of model parameters. It may be coupled with additional techniques, such as the use of Bayesian methods (Kemp-Benedict, 2010) or fuzzy logic (Alcamo, 2008).

Documentation and sharing of RAPs and scenarios

In the spirit of "*shared* socio-economic pathways", one of the goals of socio-economic pathway and scenario development is to create public goods that may be shared to facilitate many applications. Moreover, as we noted above, an important challenge in pathway and scenario design is addressing the aggregation and disaggregation or downscaling problems. An iterative, parallel process of global and regional RAP development would be a way to address this problem in place of mechanistic downscaling. To facilitate this process, it is essential for RAPs and scenarios to be created, documented, and made accessible at low cost to the research community. There are various possible ways for this process to be implemented. Various organizations could archive scenarios and make them publicly available (e.g., AgMIP: www.agmip.org). Data storage systems such as the Dataverse Network may be available. An approach for both global SSPs as well as sector-specific pathways needs to be developed by the research community.

RAPs Developed by AgMIP's Regional Teams in Sub-Saharan Africa and South Asia

One of the key components of AgMIP's regional integrated assessment framework is the development and implementation of RAPs (see Fig 3, and Part 1, Chapter 2 in this volume). AgMIP regional research teams (RRTs) in Sub-Saharan Africa and South Asia are developing and implementing RAPs to incorporate future biophysical and socio-economic conditions into their regional impact and adaptation assessments

reported in this book. In this section we summarize these RAPs and discuss issues about the development process, outcomes, and future plans as reported by the RRTs.

Regional RAPs and higher-level pathways

As discussed above, RAPs should be designed to be linked to global socio-economic pathways in a logical hierarchical structure (see Fig. 4). AgMIP RRTs have created RAPs that are consistent with SSP 2 (O'Neill, 2012) for the mid-century (2040–2069) period of analysis. Regional RAPs must incorporate trends (e.g., yield and price trends) to translate current production systems into the future conditions defined by the RAPs. Ideally this information should come from global RAPs and global economic models, however global RAPs have not yet been developed beyond the single global RAP utilized by Nelson *et al.* (2014) for harmonization purposes. The teams have used data from the IMPACT global model, which was part of an intercomparison of nine global AEMs. This activity was led by AgMIP and is currently being used as the basis for the development of global RAPs and global impact assessments. Some of the RRTS have also used information from multi-country scenarios developed by CGIAR Climate Change, Agriculture, and Food Security (CCAFS) program for East and West Africa and South Asia (Chaudhury *et al.*, 2012).

Type of RAPs

The strategy for designing regional RAPs was to start with a RAP that represents the case of BAU or current trends continued. Depending on the current conditions, stakeholders' perspectives and research from scientists that participated in the RAP development, the resulting narratives represented trends for higher or lower rates of economic development. The results show that in most cases the teams have developed higher development pathways that would be consistent with the description of RAP 2 in Fig. 5 (see Table 1 at the end of this chapter).

RAP development process

Most of the teams have followed the iterative approach to develop RAPs (see above). They have held between two to three meetings to develop one RAP; they used the first meeting to define a list of key indicators and to assign lead persons to conduct research on each indicator. A second meeting was focused on presenting findings and discussing the storylines for each indicator. In some cases, this meeting included external researchers or invited experts and stakeholders. A third meeting was organized to present the RAPs to stakeholders and obtain their feedback. In some cases (such as the Pakistani and CLIP teams), stakeholders were involved

earlier in the process of RAPs (see Table 2 at the end of this chapter). In addition some teams have organized a fourth meeting to revise and finalize the RAP and also to conceptualize and begin the process to develop alternative RAPs.

RAP narratives, key variables and trends

Table 3 (at the end of this chapter) shows the full RAP narratives developed by the RRTs in Sub-Saharan Africa and South Asia. These narratives have several interesting points in common. They all emphasize the key role of governments and agricultural policy. Public and private investment in research and development is also a key element of future socio-economic conditions. These RAPs also express a high level of concern about soil-degradation and water-availability issues and the expectation that technological improvements (e.g., improved cultivars) will help to offset the negative consequences of those biophysical conditions and the possible impacts of climate change.

RRTs have identified several key indicators to describe the future biophysical and socio-economic conditions, although good records of current trends for many indicators proved difficult to obtain. Table 4 (at the end of this chapter) shows the main indicators and their trends expressed in terms of direction (decrease, increase, no change) and magnitude (small, medium, large). Soil degradation has been consistently identified as a major issue by all the teams, which indicates that soil degradation rates will generally increase. However, the magnitude of change varies across cases; for example the magnitude is small in cases where there is more government investment in agriculture, promotion of better soil conservation activities, and increased fertilizer use. Note that these policies help to reduce the rate of soil degradation but do not reverse those conditions completely, except in a few cases where teams have developed a second, more optimistic RAP.

Another important indicator is the increased incidence of pests and diseases. This is particularly interesting because the effects of pests and diseases are not represented in most crop and livestock simulation models. By including these effects in the RAPs (based on secondary information) they can be translated into model parameters and represented in scenarios.

Other farm and household characteristics such as farm size and household size have also been identified as key variables in the RAPs, however the trends vary across cases. Farm size is one of the variables that have been under debate among researchers in each team. In most cases, farm size tends to increase due to farm consolidation and increased off-farm opportunities, which also causes a decrease in household size. This also explains why most of the teams identified increasing trends in off-farm income.

Another set of key variables are the ones related to production inputs, such as fertilizer. In most cases the teams have identified a tendency to increased use of

fertilizer due to a combination of lower fertilizer prices (usually tied to government subsidies), increased fertilizer availability, and improved information and extension services. Similarly, the use of improved crop varieties and livestock breeds is likely to increase in most cases.

Other indicators that have also been identified as important in the RAP discussions are the availability of better information and investment in extension and technical services. Most of the teams believe that there is a positive trend in relation to access to better information that could help farmers to make better-informed decisions.

Use of RAPs: Model parameterization

Following the AgMIP approach for integrated assessment of climate change impacts and adaptation (see Fig. 3 and Part 1, Chapter 2 in this volume), the teams have used the RAP information in answering Core Question 2 ("What is the impact of climate change on future agricultural production systems?") and Core Question 3 ("What are the benefits of climate change adaptation?"). Crop, livestock, and economic model parameters have been modified to represent future biophysical and socio-economic conditions (see Part 2, Chapters 1–10 in this volume for specific details). The RRTs used the DevRAP matrix to document the parameter changes, and background and related information. The process of model parameterization was also an iterative process between the teams and the AgMIP economic leaders.

In order to have a better understanding of the parameterization process, two types of variables have been identified in the RAP narratives: Variables that have *direct impacts* on one or more model parameters and variables that have *indirect impacts* on model parameters. For example, increased fertilizer use will affect directly crop model parameters (e.g., amount of mineral fertilizer applied), and economic model parameters (e.g., production costs). Similarly, reduced mineral-fertilizer prices will directly affect the economic models (production costs). On the other hand, policies such as subsidies, investment in infrastructure, and better market access do not have a direct effect on specific model parameters, but help to support the RAP narrative and explain why model parameters such as fertilizer price and fertilizer use are changing.

Stakeholder involvement

A key element of RAPs is the stakeholder involvement in the research process as this increases the legitimacy and credibility of the project activities, in particular of the RAP development. Understandably, in some cases it was challenging to engage stakeholders in a complex modeling activity. However, stakeholder participation in the RAP development process is considered one of the most successful outcomes

of the RRT activities by team members (see Table 5 at the end of this chapter). Stakeholders concerns about future conditions (e.g., food security) were a key motivation for them to contribute with their expertise and ideas to develop the RAP narratives. Stakeholders found the RAPs to be an efficient way to link scientists to policymakers, and also a good tool to be used to inform policymaking (Table 5).

Challenges, issues, and positive outcomes

The teams have identified several challenges and issues during the process of creating RAPs. Table 5 shows the challenges and positive outcomes in relation to the process of RAP development.

Identification of indicators: The first challenge that the teams faced was to identify key indicators to describe the RAP. This was particularly difficult due to the fact that developing RAPs is a new approach, and it took some time to understand the process and the ultimate goal of RAPs as a key element in the integrated assessment framework. Nevertheless, the teams were able to identify key indicators and several are common to all the teams. This shows consistency in terms of the perception about what are the key issues of the production systems being modeled even across the diverse agricultural systems of Sub-Saharan Africa and South Asia.

Data availability: Storylines must be accompanied by background information based on current studies, data, or other secondary information. It was challenging for the teams to find reliable data (e.g., current trends of key RAP elements in Table 4), in particular, data at the regional level for non-modeled activities in the production system. The teams recognize that obtaining better data is a point for future improvement.

Agreement on trend directions and magnitudes: The teams have reported that reaching an agreement about the direction and magnitude of changes of indicators was difficult. Disciplinary bias, personal convictions or interests, and little understanding of RAPs were mentioned as the main reasons. For example, some people thought about future conditions as "predictions" of what they think will happen rather than making projections consistent with a narrative to describe plausible future conditions. Reaching agreement for the magnitude of change was more difficult compared to the direction of change. As a next step, the teams will revise those storylines where agreement levels were low by conducting additional research or inviting an expanded group of experts. Sensitivity tests will also help identify parameters and specific trends where particular care must be taken to prevent unrealistic results.

Interaction with stakeholders: The teams reported that one of the most challenging issues was the initial interaction with stakeholders. In particular, explaining the RAP framework and its use within the modeling approach was very difficult. However,

most of the teams reported that they succeeded in engaging the stakeholders in the RAP process and obtaining good feedback from them due to multiple meetings and relationship-building.

Despite the challenges faced in developing RAPs, the main positive outcome of the teams is that they succeeded in creating at least one RAP for their region. The RRTs were able to form multi-disciplinary and multi-institutional teams of scientists and involve experts outside of their research teams and stakeholders and come to a level of agreement of what could be a plausible future. The RRTs reported that another positive outcome was the better understanding of how the RAPs fit the integrated assessment framework thanks to the last step of reviewing the RAPs and the model scenarios in conjunction with the AgMIP regional economics team. The teams feel more confident now about developing alternative RAPs and incorporating these into their analysis, which is fertile ground for continuing study.

The way forward: All the RRTs have reported plans for improving the RAPs that had been developed by doing further research on key variables. They will continue developing alternative RAPs for the same region where they developed the first RAP. In addition, RRTs plan to develop RAPs for other regions in their countries. In all cases, the teams are planning to increase stakeholder participation in the next set of project activities and to involve them early in the process.

The AgMIP economic leadership plans to revise the RAP process methodology and tools, create a master list of indicators with detailed definitions that can facilitate the development of RAPs (as noted above, a key issue was to identify main indicators), and provide standard definitions of the indicators being used in the RAPs. AgMIP will also develop ways to archive and document the RAPs and related information in a way that can be used by other researchers.

Conclusions

This chapter presents the conceptual foundations and methods for designing representative agricultural pathways (RAPs) and scenarios that can be coupled with global socio-economic pathways (i.e., SSPs) for agricultural model intercomparison and improvement, and for climate impact, adaptation, and vulnerability assessment, as envisaged by AgMIP and other global and regional modeling projects. AgMIP's goal is to design RAPs for all of the major agricultural regions of the globe. The first step in this process began with regional impact assessment teams created by AgMIP in collaboration with national and international institutions in Sub-Saharan Africa and South Asia (see www.agmip.org). Developing RAPs for these teams has been a "learning by doing" process that has created the capability for better communication and understanding across disciplines and between scientists and stakeholders.

As the regional teams create additional RAPs and implement integrated assessments at the regional and local scales, it will be possible to scale them up to the national and global levels, thus leading to a consistent set of linked global and regional RAPS. These accomplishments will enable a new capability by the agricultural modeling community to conduct agricultural model intercomparisons, and impact, adaptation, and vulnerability assessments consistently across scales. We are confident that this capability will lead to the improvement of agricultural models and to a new generation of improved global and regional assessments.

Annex 1 — Tables

Table 1. RAPs location and type.

Regional research team	Location	Rate of economic development	Stakeholder involvement
CLIP	Zimbabwe, Matabeleland	High	Yes
CLIP	Zimbabwe, Matabeleland	Low	Yes
CLIP	Mozambique, Manica	High	Yes
CLIP	Mozambique, Manica	Low	Yes
East Africa	Kenya, Embu	High	Yes
SAMIIP	Namibia	High	Yes
SAMIIP	South Africa	High	Yes
CIWARA	Senegal, Nioro	Low	Yes
CIWARA	Senegal, Nioro	High	Yes
South India	India, ANGRAU	High	Some
South India	India, Tamil Nadu	High	Yes
IGB	India, IGB	Low	Yes
IGB	Nepal, IGB	High	No
Pakistan	Pakistan, wheat–rice region	High	Yes
Sri Lanka	Sri Lanka, Kurunegala District	High	Yes
Sri Lanka	Sri Lanka, FECT	High	Yes

Low: Low rate of economic development
High: High rate of economic development

Table 2. RAP development process.

AgMIP RRT	RAP lead person	RAP #	Meeting #	Type of meeting	Goal	Number of attendees	Number of stakeholder attended	Used a facilitator? If yes, name	Status of RAP
IGB India	Harbir Singh	2.1	1	Research team and other scientists	Identify variables to be used in TOA-MD	9	0	Yes, Singh	Regional RAPs (district level) developed. It needs to be updated further for the state as well the whole IGB area (including Nepal and Bangladesh)
		2.1	2	Research team, experts and stakeholders	Explain RAPs and have feedback from stakeholders	29	7	Yes, Singh	
South India	Paramasivam	2.1	1	Research team	Identify variables	8	0	No	RAP process initiation, identification of potential variables, literature review
		2.1	2	Research team, experts	Develop initial RAP narrative	25	0	Balasubramanian	Preliminary RAPs developed for presentation to stakeholder views
		2.1	3	Research team, experts, stakeholders, farmers	Finalize RAP narrative	35	15	Suresh	RAP narrative discussed with participants and finalized
East Africa (Kenya)	Richard Mulwa	2.1	1	Research team	Identification of variables and initial discussions on directions and magnitude of changes	5	0	Mulwa	Variables identified and initial narrative developed, then circulated to research team for further comments

(*Continued*)

Table 2. (*Continued*)

AgMIP RRT	RAP lead person	RAP #	Meeting #	Type of meeting	Goal	Number of attendees	Number of stakeholder attended	Used a facilitator? If yes, name	Status of RAP
		2.1	2	Research team and other experts	Discussion on the magnitudes and direction of variables identified by the research team	15	1	Mulwa/KPC Rao	Initial narrative refined, experts gave opinion and RAP adjusted to fit discussions between experts and research team
		2.1	3	Research team and stakeholders	Clarification on the figures in the RAPs and further comments from stakeholders	25	20	Mulwa	Stakeholder gave opinions on the directions and magnitudes of some variables and we got consensus. Now RAP fully developed
CLIP	Sabine Homann	2.1	1	Research team meets and email exchange	Revise background material, identify variables and define the process of conducting the RAPs	3	0	No	We developed two draft narratives about different scenarios, compared both for consistency, but use only 1.1 for the analysis. Feedback from Roberto Valdivia was used to revise that narrative and verify again with experts
		2.1	2	Research team and stakeholders (crops, livestock, extension)	Report research and assess RAPs with experts	6	4	No	

(*Continued*)

Table 2. (*Continued*)

AgMIP RRT	RAP lead person	RAP #	Meeting #	Type of meeting	Goal	Number of attendees	Number of stakeholder attended	Used a facilitator? If yes, name	Status of RAP
		2.1	3	Research team and stakeholders (crops, livestock, extension)	Document RAPs and share with stakeholders for feedback	6	4	No	
		2.1	4	Research team	Develop final RAP narratives and plan for next RAPs	2	0	No	
		2.2	5	Research team and stakeholders (crops, livestock, extension)	Report research and assess RAPs with experts	6	4	No	
		2.2	6	Research team and stakeholders (crops, livestock, extension)	Document RAPs and share with stakeholders for feedback	6	4	No	
		2.2	7	Research team	Develop final RAP narratives and plan for next RAPs	2	0	No	
		2.1 + 2.2	8	Research team and experts	Revise final RAPs	4	0	No	
SAAMIP (Namibia)	Mogos	2.1	1	Research team and other experts	Identify variables and lead persons per indicator	9	2	No	Final narrative developed, expect to revise it further as we make progress with other RAPs or get better estimates of trends

(*Continued*)

Table 2. (*Continued*)

AgMIP RRT	RAP lead person	RAP #	Meeting #	Type of meeting	Goal	Number of attendees	Number of stakeholder attended	Used a facilitator? If yes, name	Status of RAP
Sri Lanka Rice Team	R. M. Herath	2.1	1	Research team	Study global and regional RAPs and discuss variables to be considered and identify experts and stake holders to be invited for the meeting and lead persons for variables/areas	11		No	Final narrative developed, expect to revise it further as we make progress with other RAPs or get better estimates of trends
			2	Research team and university academics, research officers, and leading stakeholders	Improve awareness on AgMIP project and get views on climate change impacts on rice farming	77	70	Facilitated by the administrative lead of the AgMIP project	
			3	Research team and university academics, research officers, leading stakeholders, and respective Ministry representative	Discuss views obtained by leading stakeholders to develop RAP needs and possible adaptation strategies	25	19		
		2.1	4	Research team, other experts, and stakeholders	Develop RAPs with the participation of invited experts and stakeholders	98	90		

(*Continued*)

Table 2. (*Continued*)

AgMIP RRT	RAP lead person	RAP #	Meeting #	Type of meeting	Goal	Number of attendees	Number of stakeholder attended	Used a facilitator? If yes, name	Status of RAP
		2.1	5	Research team, selected lead experts and stakeholders	Explain RAPs developed at the previous meeting and have feedback from experts and stakeholders	15	4	No	
		2.1	6	Research team	Develop final RAP narratives and plan for next RAPs	11		No	
IGB-Nepal	D.B. Thapa Magar	2.1	1	Research team	Identify key variables affecting production system in the future	6	0	No	Draft narrative of RAPs is developed and is still in the process of refinement for getting better estimates of the various variables taken into consideration.
		2.1	2	Research team and multi-disciplinary experts	Sharing about RAPs and discussion with experts	14	0	Yes, D. B. Thapa Magar	
		2.1	3	Research team and stakeholders	Explain RAPs and have feedback from stakeholders	12	8	Yes, D. B. Thapa Magar	
		2.1	4	Research team	Develop (and review) final RAP narratives	3	0	No	

(*Continued*)

Table 2. (*Continued*)

AgMIP RRT	RAP lead person	RAP #	Meeting #	Type of meeting	Goal	Number of attendees	Number of stakeholder attended	Used a facilitator? If yes, name	Status of RAP
Pakistan	M. Ashfaq	2.1	1	Research team	1. Identify variables for different categories 2. Identify lead persons per indicator	10	0	No	Narratives have been developed and revised for current RAP, scenarios have been quantified in the light of developed RAPs and trends have been guesstimated, based on facts and trends
		2.1	2	Research team, other experts, and stakeholders	Report research proposal and discuss each variable according to DevRAP matrix format with experts and stakeholders for their feedback	25	5	Yes, Dr. Abdus Saboor, Dr. Abdul Qudus and Dr. Mrs. Sofia Anwar	
		2.1	3	Research team, other experts, and stakeholders	Discuss variables inconsistencies and have feedback on them from experts and stakeholders	30	10	Yes, Dr. Abdus Saboor, Dr. Abdul Qudus, and Dr. Mrs. Sofia Anwar	
		2.1	4	Research team	Finalize the RAP narratives and discuss about future RAPs	10	0	No	

Table 3. AgMIP regional research teams RAP narratives.

Region and RAP code	RAP narrative
Zimbabwe, Matabeleland — 2.1	***The pessimistic RAP: If there is no change of mindset and way of doing business, food security situation will continue to worsen*** Opportunities for massive increases in agricultural production and productivity exist but are not being exploited. Persisting economic crisis, governments extractive policies (high taxes), and lack of incentives and security for private-sector investment hinder development. Agricultural production and profitability are declining, land is degrading and being underutilized. Labor migration and HIV/AIDS result in labor shortage. Agricultural inputs are in short supply and expensive. Use of improved cultivars will force further decline. With the high cost of production, food imports will further reduce farmers' chances to make a living from agriculture. Poverty levels continue to increase, people become more vulnerable to food insecurity and other risks.
Zimbabwe, Matabeleland — 2.2	***The positive RAP: Zimbabwe stepping out of crisis: For agricultural growth to happen, this depends on the strong assumptions that favorable conditions for private and public investments in the agricultural sector will be created*** Government policy objective is to achieve food security, ensure adequate raw materials for the manufacturing sector and increased export earnings through increased productivity, efficient input use, improved investment and market access, infrastructure, and service development, targeting annual agricultural growth of 9.1% by 2015. A proactive legislation will stipulate land-tenure security, incentives for the banking sector, and revamp research and extension to promote productivity-enhancing technologies for adoption on a large scale. The transformation however starts under extremely difficult conditions, characterized by large account deficit and liquidity challenges and limited direct foreign investment due to lack of clarity on investment security and high interest rates. Underfunded public sector and underperformance of the private sector limit development of the agricultural sector and result in unsustainable import bills for agricultural commodities. Limited employment opportunities in urban areas have curtailed rural–urban migration. Most people remain in rural areas where agriculture is the main livelihood activity due to lack of alternatives.
Mozambique, Manica — 2.1	***Pessimistic RAP: We are about to unlock the potential for growth through market-oriented crop and livestock production*** Government and state policies invest in extractive industries, also with an aim to uplift agriculture and food security. In agriculture, government promotes market-oriented production; subsidies are only during recovery and rehabilitation. Poor infrastructure is a major barrier to agricultural development. Investment in infrastructure is, however, slow. Poor road construction and maintenance restrict private-sector investments in these high-potential agricultural areas (for crops and livestock). Farmers produce beyond subsistence, but fail to access profitable markets (inputs and outputs). Lack of competition input prices tend to be high, output prices generally low. Limited financial capacities and low education levels further restrict farmers' ability for higher benefits from increased agricultural production.

(*Continued*)

Table 3. (*Continued*)

Region and RAP code	RAP narrative
Mozambique, Manica — 2.2	***Optimistic RAP: Expected funding for market-oriented crop and livestock production will be realized*** PEDSA (national strategic plan) will be funded by 2015 and various investment programs will be implemented. Donors' conferences will mobilize resources for funding. PNISA (strategy area in PEDSA, National Investment for Agriculture) will define the requirements for developing the agricultural sector (public/private). Other programs are the Beira Agricultural Growth Corridor for small to medium companies. Private-sector development will be through CEPAGR, infrastructure development through PROIRRI.
Kenya, Embu — 2.1	***Maize production in Embu, Kenya amidst several challenges*** A combination of increasing population, government plans to invest in fertilizer factory, government subsidy on fertilizers, improved economic performance expected to cause a shift from agriculture to service industry, government plans for massive expansion of irrigation (irrigate 1 million ha.), newly devolved county governments etc. are some of the developments expected to change agriculture development in the country.
Senegal, Nioro — 2.1	***Crop production in Nioro with short-term agricultural-policy intervention*** This RAP assumes dominance of state actors in the agricultural-development agenda with the view to bring in fast short-term gains with food-security outcomes to the population. Main interventions will include support for the agricultural-service sector, fertilizer subsidies, and feeder roads (slow). Trading land and human resources to foreign investors, who will in turn develop infrastructure.
Senegal, Nioro — 2.1	***Nioro RAP*** Both the state and the local private sector recognize the need to pursue long-term development in the agricultural sector. Organized civil society demands are factored in. The transformative path will lead to emerging agricultural powerhouse in West Africa with reliance on strong agro-dealers and satisfactory solutions to consumer preferences.
South Africa — 2.1	***Increased commercial agricultural production supported by successful land reform and improved socio-economic conditions*** Agricultural and land-reform policies focus on supporting commercial agricultural production and productivity. Better and well-functioning agricultural credit and market services for both established and emerging farmers. Increased uptake of adaptation strategies by commercial farmers.
Namibia — 2.1	***Higher expectations for agricultural production in the face of continued environmental and socio-economic challenges*** Unintended government policy consequences; lack of good farm management practices specifically to biophysical conditions of land lead to small benefit to the livelihoods. Labor migration to urban areas, non-agricultural activities and impact of HIV/AIDS also leads to labor shortages. Agricultural inputs are not affordable for small-scale farmers. With increases in poverty levels people become more vulnerable to climate change and other risks.

(*Continued*)

Table 3. (*Continued*)

Region and RAP code	RAP narrative
Pakistan, Rice–Wheat Zone of Punjab — 2.1	***Rice–wheat production under vulnerable climatic conditions*** Agriculture production is very important to ensure food security and provision of employment opportunities to the majority of the rural population. Therefore, the government is committed to supporting the agriculture sector through increased public investment to fulfill the needs of an increasing population. The governmental policy objective is to achieve food security, ensure adequate raw materials for the manufacturing sector, and increased export earnings through increased productivity, efficient input use, and better market access, infrastructure, and service development. A proactive legislation will stipulate land-tenure security and incentives for the banking sector and revamp research and extension to promote productivity-enhancing technologies for adoption on a larger scale. The adoption process will be instigated due to the anticipated losses in agricultural productivity in the face of climatic uncertainties.
Sri Lanka, FECT — 2.1	***Government sector plans and policy work for rice-sector improvements*** The government aims to improve food security through self-sufficiency in rice with a framework to promote the rice sector to cope with impacts of variable climate. The government promotes high-yielding and drought-/flood-tolerant rice varieties with policy to encourage the application of organic fertilizers, decreasing the cost on inorganic fertilizers. Government puts more emphasis on improving the agricultural water irrigation/management system to cope with drought conditions.
Sri Lanka, Kurunegala — 2.1	***Intermediate adaptation challenge for increased rice production*** The government aims to invest more in agriculture, shortage of labor with the consequence of decreased population growth and household size. The government promotes improved cultivar and climate-smart technologies but the policy to cut down the use of inorganic fertilizer and phase out the fertilizer subsidy results in deteriorating biophysical conditions, low use of inorganic fertilizer, less water, reduced farm sizes which lead to low benefit from the improved cultivar.
North India, IGB — 2.1	***Cereals-production system under climate change*** Climate change has an adverse impact on agricultural production system in the Indo-Gangetic region where rice–wheat is the predominant cropping system, which contributes to national food security. Global trends suggest that rice–wheat production in the region will be adversely affected by climate change. Though the government adopts long-term and short-term policy measures, rice–wheat production costs increase substantially. Imports are inadequate to meet domestic demand. Incentives in the form of assured prices (minimum support prices) are inadequate to enhance agricultural production to meet food demand. Hence, government liberalizes imports of food grains, invests in food chain logistics, and boost research and development for new crop cultivars to boost agricultural production for ensuring food security.

(*Continued*)

Table 3. (*Continued*)

Region and RAP code	RAP narrative
Nepal, Banke — 2.1	***Climate change impacts and adaptation strategies for rice–wheat production system in Terai region of Nepal*** Climate change remains as a key challenge for a country like Nepal where subsistence-based and rainfed agriculture system is dominant. Heavy reliance on suitable climatic conditions for agricultural production always imposes serious risk to the agricultural sector in Nepal. On the other hand, having limited capacity to adapt and respond to the climatic stresses, rural poor farmers in the country face the challenge of adapting to climate change impacts. However, the government will prioritize its programs to minimize the loss from climate change impacts and reduce the vulnerability of the people. Along with the support programs such as agricultural insurance and input subsidies, the government efforts and investments will be increased for extending irrigation services, agricultural mechanization, and developing disaster risk-management practices. The support for agricultural research, education, and extension programs will also be increased for developing and disseminating climate change adaptation agricultural technologies to the farmers. This will support them as they adapt to climate change and reduce their vulnerability.
South India, Tamil Nadu — 2.1	***RAPs for Tamil Nadu*** There will be a small increase in crop diversity due to the need to combat the climate and market risks as both of these might become more volatile in the future. Water quality and water availability for agriculture will decrease due to pollution of water bodies, and competition for water from other sources, but water-use efficiency in agriculture will increase due to technological progress. Soil quality will decline by a small-to-medium extent, due to pollution, and intensive cultivation will be caused by a shrinking land base for agriculture. Most subsidies are likely to decline while prices of agricultural commodities will increase. Farm size and wage rates will increase. Mechanization and energy-use intensity in agriculture will increase. Share of agriculture in overall economy will decrease with increase in inequality. Significant decline in poverty will be associated with a decrease in family size and increase in non-farm income. There will not be significant changes in food imports, while yield of important crops will increase due to technological progress in agriculture. Fertilizer-use intensity and fertilizer productivity will increase. Corporate role in agriculture will increase with improved increase in commodity groups.
South India, Andhra Pradesh — 2.1.1	***Maize production in India*** With a high cost of production and degraded natural resources, profitability in agriculture may be further reduced, making agriculture unprofitable. This requires more opportunities in non-agricultural income and increased technological interventions. However, opportunities for massive increases in agricultural production and productivity exist. Use of improved cultivars and mechanization will be increased and use of critical interventions may lead to increases in productivity and efficient use of resources.

Table 4. AgMIP regional research teams RAP trends.

Sub-Saharan Africa teams

Variable	CLIP – R1 Zimb	CLIP – R2 Zimb	CLIP – R1 Mozamb	CLIP – R2 Mozamb	East Africa Embu, KE	West Africa R1 Nioro	West Africa R2 Nioro	SAAMIP South Africa	SAAMIP Namibia
Soil degradation	↘	↗	↗	→	↗	↗	↘	↗	↗
Pest and diseases	⬢	⬢	⬢	⬢	→	⬢	⬢	⬢	⬢
Extreme events	↗	↗	⬢	⬢	↗	⬢	⬢	⬢	⬢
Water availability	⬢	⬢	⬢	⬢	↘	⬢	⬢	↘	↘
Farm size	↘	↘	→	→	↘	↗	↗	↗	↘
Household size	↗	→	→	→	↗	↘	↘	⬢	↘
Herd size	↗	↘	→	↗	⬢	↗	↘	⬢	⬢
Livestock Productivity	↗	↘	→	↗	⬢	↗	↗	⬢	⬢
Fertilizer prices	→	↗	↘	↘	↗	→	→	⬢	⬢
Fertilizer use	↗	↘	↘	↗	↗	⬢	⬢	↗	↗
Subsidies (inputs)	↗	→	→	→	⬢	→	↘	⬢	⬢
Off-farm income	↘	↘	↗	↗	↗	↗	↗	↗	↘
Improved crop use	↗	↘	→	↗	⬢	↗	↗	↗	→
Information availability	⬢	⬢	⬢	⬢	↗	⬢	⬢	⬢	⬢
Public invest in Agriculture	↗	→	↘	↗	⬢	⬢	⬢	↗	→
Labor availability	→	↘	↗	↗	↘	⬢	⬢	⬢	⬢

Direction and magnitude	
No change	→
Small increase	↗
Moderate increase	↗
Large increase	↗
Small decrease	→
Moderate decrease	↘
Large decrease	↘
Not included in RAP or under revision	⬢

South Asia teams

Variable	Pakistan	Sri Lanka - FECT	Sri Lanka - Kuneg	IGB North India	IGB Nepal	South India TNAU	South India ANGRAU
Soil degradation	↗	↗	↗	↗	↗	↗	↗
Pest and diseases	↗	⬢	⬢	⬢	↗	↘	↗
Extreme events	↗	↗	⬢	⬢	↗	⬢	↗
Water availability	↘	⬢	↘	⬢	⬢	⬢	↘
Farm size	↘	⬢	↘	↘	↘	↗	↗
Household size	↗	↘	↘	↘	⬢	↘	⬢
Herd size	↗	⬢	⬢	⬢	⬢	⬢	↗
Livestock Productivity	⬢	⬢	⬢	⬢	⬢	⬢	⬢
Fertilizer prices	↗	↗	↗	⬢	↗	↘	↗
Fertilizer use	↗	⬢	⬢	⬢	⬢	⬢	↘
Subsidies (inputs)	↗	↘	↘	→	↗	↘	↘
Off-farm income	↗	⬢	⬢	⬢	↗	↗	↗
Improved crop use	↗	↗	↘	⬢	↗	↘	↗
Information availability	↗	↗	⬢	↗	↗	⬢	↗
Public invest in Agriculture	↗	↗	↘	⬢	↗	⬢	↘
Labor availability	↘	↘	↘	⬢	↘	↘	↘

Direction and magnitude	
No change	→
Small increase	↗
Moderate increase	↗
Large increase	↗
Small decrease	→
Moderate decrease	↘
Large decrease	↘
Not included in RAP or under revision	⬢

Table 5. RAP development process, challenges, and outcomes.

Team	Challenges, issues	What worked Positive outcomes	Next steps
IGB India	The RAP development process requires a lot of patience to identify important issues/variables with help from a diverse group of stakeholders who often have divergent views/opinions.	The feedback from the scientists in the first meeting was very logical. During the second meeting, the stakeholders appreciated the process and utility of developing RAPs for a likely scenario of farming systems under climate change.	The district-level RAP is being finalized and, if approved, the team plans to update the RAP for the regional level (covering the whole IGB).
South India	Visualizing specific scenario-based RAPs.	Identification variables likely to be impacted, general directions and magnitudes of change from literature.	Arrangements for RAPs meet with interdisciplinary scientists.
	Disciplinary bias, personal convictions of experts, visualizing scenario-based future outcomes, anticipating policy changes and system changes were major challenges to arriving at a consensus.	Able to reach consensus on major variables likely to be impacted, their direction and magnitudes of change with levels of agreements and convictions.	Arrangements for wider stakeholders meet along with interdisciplinary scientists and farmers.
	Narrowing perception differences between farmers who concentrate on short-term variability issues and expert and stakeholder views on climate change.	RAP finalized. Participants were initially asked for their views and later presented with earlier RAP drafts by experts. In most cases general directions of change coincided and magnitudes were also more or less similar.	Incorporation of variables identified into integrated climate change impact assessment of agricultural-production systems.

(*Continued*)

Table 5. (*Continued*)

Team	Challenges, issues	What worked Positive outcomes	Next steps
East Africa (Kenya)	In the initial stages, it was difficult to identify the variables in each category. The broad categorization (grouping) of variables helped us. However, coming up with the relevant variables for each category was the biggest challenge. In the end we managed to agree on the variables we used in our RAP.	We managed to agree on the variables, and the research team appreciated the importance of RAPs. This enabled us to move to the next stage.	Maintain the same research team for Phase II.
	The first challenge was identifying experts with interest on climate change issues. The biggest challenge, however, was agreeing on the magnitude and directions of the different variables. The experts also helped with addition of a few variables not included in the initial stage. Agreements on the general direction were relatively easier but agreeing on magnitude was quite difficult.	Disagreement, especially on the magnitude of change was pronounced in this meeting, but finally we managed to agree on all the variables we had identified. Experts also helped with identification of more variables.	If there is any extension of the project, then we will have new RAPs for the new localities we will be working in.
	The challenge was first explaining to stakeholders why we took the direction of RAPs. Some wanted to know whether it had been applied elsewhere. Once this was clear, there were disagreements with magnitude and direction of some variables such as farm size. However at the end, there was consensus and everyone appreciated the effort.	We managed to explain to stakeholders why RAPs were necessary and they were able to appreciate our efforts in the whole process.	We promised to share the RAP with stakeholders so they can give us any extra inputs if they have.

(*Continued*)

Table 5. (*Continued*)

Team	Challenges, issues	What worked Positive outcomes	Next steps
CLIP	RAPS were a new concept, with no previous experience within the project team and limited support from other scientists. We used the comparison of RAPS for two scenarios and expanded the list of variables to verify the projections as perceived by the stakeholders. Economic leadership feedback was useful, and highlighted the need for additional expertise to verify consistency and plausibility. Stakeholders' differentiation of future scenarios with and without climate change was not possible — those differences had to be incorporated later, based on experts estimations. A limitation might be that the African socio-political systems are very dynamic and often with poor governance structures — assumptions and therewith the percentages of change can change dramatically.	To work within a limited budget we had decided for structured discussion with few knowledgeable stakeholders (mostly government staff at provincial level) to assess the RAPs, rather than a participatory multi-stakeholder workshop. The approach proved to be effective. Few variables were also verified through the private sector, e.g., expected price trends. The discussions were engaged and stimulated further thinking about the complexity, causes and effects of policy interventions on farming systems. It provided valuable information on the socio-economic context, challenges and investments, that will be useful also for other projects.	The same approach was implemented in Mozambique — the final review is outstanding. In Malawi, RAPs still need to be assessed. Cross-country comparison should give valuable insights on context specificity and complexity of development pathways.

(*Continued*)

Table 5. (*Continued*)

Team	Challenges, issues	What worked Positive outcomes	Next steps
SAAMIP Namibia	The challenge was to explain the concepts of scenario development to stakeholders. Stakeholders and experts tend to focus on their expertise area only. For example, in Namibia, where livestock is important, stakeholders would prioritize looking at the impacts of climate change on livestock and rangeland.	Each participant contributed positively to the discussion and looked at the future with objectivity.	For Namibia, for this phase of the project what we have collected is final, for the future we hope to include more RAPs.
Sri Lanka Rice Team	There was a challenge of getting the views of all, since a large number of experts and stakeholders had been invited for certain meetings. However, this was overcome by having group discussions. Since experts of different discipline were put together, everyone tried to show that variables that fell into their own discipline will be affected more than other variables. It was difficult to come to an agreement on the exact magnitude of specific variables and this highlighted the need for comprehensive investigations.	The third and fifth meetings were very successful since only selected experts and stakeholders only from the rice sector were invited. Experts and stakeholders had come with preparation and background information. They got the opportunity to discuss in detail future planning with respect to adapting to climate change, taking into consideration traditional knowledge and a systems approach.	It was expected to review these RAPs further and to develop other possible RAPs to address the challenges. It also very much highlighted the need for development of a comprehensive related database for region-/crop-/farming-system-specific information for precise predictions.

(*Continued*)

Table 5. (*Continued*)

Team	Challenges, issues	What worked Positive outcomes	Next steps
IGB Nepal	Identifying the key variables affecting the production system, estimating their direction and magnitude of change in the future and incorporating their effect in the production system is challenging.	Review of the past trends and future projections of climate, technology development, and production trends and socio-economic developments (labor issues, input and output price) and interaction with the multi-disciplinary experts and stakeholders was useful to identify and estimate the direction of changes in key variables that affect the production system.	Need further review of RAPs with consultations with the research-team members and multi-disciplinary experts to refine the various variables taken into consideration for the production-system analysis.
Pakistan	Identification of the socio-economic, agronomic, and management variables that stakeholders (policymakers, researchers, farmers, etc.) could use as adaptation option(s) and then assess the aggregate effect of these options as a package on future agriculture system in the face of climate change Unavailability of region specific *ex-ante* analytical impact assessments studies for cropping system and livestock. Minor activities and livestock (meat and milk) were included in the RAPs without modeled data (like IMPACT trends). For the future, such modeled estimates are required for generating regional-level RAPs and making them consistent with the global-level RAPs.	A multi-disciplinary team of scientists (economists, plant breeders, irrigation specialists, soil scientists, agronomists, policymakers, progressive farmers, extensionists, and other experts) was established. Based on the draft narrative parameters, a comprehensive RAP package was developed by involving the key stakeholders in the process. The draft RAP was given to experts, researchers, and the project team for their insight after discussion with their respective colleagues. Thus it helped in determining the direction and extent of the impacts imparted by these adaptation practices.	Alternative RAPs would be developed and their possible impacts would be analyzed. For the mixed, cotton–wheat and rainfed cropping zones, RAPs will also be developed and impacts will be assessed. Alternative RAPs will be developed for these cropping zones and comparisons of these RAPs could also be made for best RAP selection. Continuous feedback from the policymakers and other stakeholders will be sought in order to refine the adaptation packages and quantify their impacts.

(*Continued*)

Table 5. (*Continued*)

Team	Challenges, issues	What worked Positive outcomes	Next steps
		Final regional RAPs were used by crop and economic modeling teams for scenario development, parameters, and trend quantification. These regional RAPs developed by the AgMIP-Pakistan team for rice–wheat cropping system could be used for other impact assessment studies in the future.	Different meetings have been planned to be organized at the Food and Agriculture Wing, Planning Commission Islamabad, Punjab Economic Research Institute Lahore, and in other educational and research institutes of the Province.

Source: AgMIP regional research teams.

References

Alcamo, J. (2008). "The SAS Approach: Combining Qualitative and Quantitative Knowledge in Environmental Scenarios", in Alcamo, J. (ed.), *Environmental Futures*, Elsevier, Amsterdam, pp. 123–150.

Antle, J. M. (2011). Parsimonious Multidimensional Impact Assessment, *Am. J. Agric. Econ.*, **93**, 1292–1311.

Antle, J. M., Stoorvogel, J. J., and Valdivia, R. O. (2014a). New parsimonious simulation methods and tools to assess future food and environmental security of farm populations, *Phil. Trans. Roy. Soc. B*, **369**, 20120280.

Antle, J. M. and Valdivia, R. O. (2011). *TOA-MD 5.0: Tradeoff Analysis Model for Multi-Dimensional Impact Assessment*. Available at: http://tradeoffs.oregonstate.edu. Accessed on 21 March 2014.

Antle, J. M., Valdivia, R. O., Claessens, L., Nelson, J., Rosenzweig, C., Ruane, A. C., and Vervoort, J. (2014b). *Designing Sectoral and Regional Pathways and Scenarios for Climate Impact Assessment: Lessons from the Agricultural Model Inter-comparison and Improvement Project*. Available at: http://tradeoffs.oregonstate.edu. Accessed on 21 March 2014.

Carter, T., Ebi, K., Edmonds, J., Hallgatte, S., Kriegler, E., Mathur, R., O'Neill, B., Riahi, K., Winkler, H., van Vuuren, D., and Zwicke, T. (2012). "A framework for a new generation of socioeconomic scenarios for climate change impact, adaptation, vulnerability, and mitigation research", in Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Barros, V., Field, C. B., Zwickel, T., Schloemer, S., Ebi, K., Mastrandrea, M., Mach, K., and von Stechow, C. (eds.), *Workshop Report of the Intergovernmental Panel on Climate Change Workshop on Socio-Economic Scenarios*, IPCC Working Group III Technical Support Unit, Potsdam Institute for Climate Impact Research, Potsdam Germany, p. 51.

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., Jäger, J., and Mitchell, R. (2003). Knowledge systems for sustainable development, *Proc. Natl. Acad. Sci. U. S. A*, **100**(14), 8086–8091.

Chaudhury, M., Vervoort, J., Kristjanson, K., Ericksen, P., and Ainslie, A. (2013). Participatory scenarios as a tool to link science and policy on food security under climate change in East Africa, *Regional Environmental Change*, **13**(2), 389–398.

Easterling, W., Aggarwal, P. K., Batima, P., Brander, K. M., Erda, L., Howden, S. M., Kirilenko, A., Morton, J., Soussana, J.-F., Schmidhuber, J., and Tubiello, F. N. (2007). "Food, fibre and forest products", in Parry, M. L. (ed.), *Climate Change 2007: Impacts, Adaptation and Vulnerability*, Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, pp. 273–313.

Ewert, F., van Ittersum, M. K., Heckelei, T., Therond, O., Bezlepkina, I., and Andersen, E. (2011). Scale changes and model linking methods for integrated assessment of agri-environmental systems, *Agric., Ecosyst. Environ.*, **142**, 6–17.

Gaffin, S. R., Rosenzweig, C., Xing, X., and Yetman, G. (2004). Downscaling and geo-spatial gridding of socio-economic projections from the IPCC Special Report on Emissions Scenarios (SRES), *Global Environ. Change*, **4**, 105–123.

Havlík, P., Schneider, U. A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., and Aoki K. (2011). Global land-use implications of first and second generation biofuel targets, *Energy Policy*, **39**(10), 5690–5702.

Havlík, P., Valin, H., Herrero, M., Obersteiner, M., Schmid, E., Rufino, M. C., Mosnier, A., Thornton, P. K., Böttcher, H., Conant, R. T., Frank, S., Fritz, S., Fuss, S., Kraxner, F., and Notenbaert, A. (2014). Climate change mitigation through livestock system transitions, *Proc. Natl. Acad. Sci.*, **111**(10), 3709–3714.

Kemp-Benedict, E. (2010). Converting qualitative assessments to quantitative assumptions: Bayes' rule and the pundit's wager, *Technol. Forecast. Soc.*, **77**, 167–171.

Kriegler, E., Edmonds, J., Hallegatte, S., Ebi, K. L., Kram, T., Riahl, K., Winkler, H., and van Vuuren, D. P. (2014). A new scenario framework for climate change research: the concept of shared climate policy assumptions, *Clim. Change*, **122**(3), 401–414.

Kriegler, E., O'Neill, B. C., Hallegatte, S., Kram, T., Lempert, R. J., Moss, R. H., and Wilbanks, T. (2012). The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways, *Global Environ. Change*, **22**(4), 807–822.

International Institute for Applied Systems Analysis (2012). *SSP Database*. Available at: https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd?Action=htmlpage&page=about#intro. Accessed on 10 December 2012.

Merel, P. and Howitt, R. (2014). Theory and application of positive mathematical programming in agriculture and the environment, *Ann. Rev. Resource Econ.*, **6**(1), 451–470.

Moss, R., Babiker, M., Brinkman, S., Calvo, E., Carter, T., Edmonds, J., Elgizouli, I., Emori, S., Erda, L., Hibbard, K., Jones, R., Kainuma, M., Kelleher, J., Lamarque, J. F., Manning, M., Matthews, B., Meehl, J., Meyer, L., Mitchell, J., Nakicenovic, N., O'Neill, B., Pichs, R., Riahi, K., Rose, S., Runci, P., Stouffer, R., van Vuuren, D., Weyant, J., Wilbanks, T., van Ypersele, J. P., and Zurek, M. (2008). *Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies*, Intergovernmental Panel on Climate Change, Geneva, p. 132.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and 1183 assessment, *Nature*, **463**, 747–756.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grübler, A., Jung, T. Y., Kram, T., La Rovere, E. L., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Riahi, K., Roehrl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M., Shukla, P., Smith, S., Swart, R., van Rooijen, S., Victor, N., and Dadi, Z. (2000) in Nakicenovic, N. and Swart, R. (eds.), *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, p. 599.

Nelson, G., Rosegrant, M. W., Palazzo, A., Gray, I., Ingersoll, C., Robertson, R., Tokgoz, S., Zhu, T., Sulser, T. B., Ringler, C., Msangi, S. and You, L. (2010). *Food security, farming, and climate change to 2050: Scenarios, results, policy options*, IFPRI, Washington, DC, p. 155. Available at: http://www.ifpri.org/sites/default/files/publications/rr172.pdf. Accessed on 12 March 2014.

Nelson, G. C., van der Mensbrugghe, D., Hasegawa, T., Takahashi, K., Sands, R., Kyle, P., Calvin, K., Havlik, P., Valin, H., Mason d'Croz D., Kavallari, A., Tabeau, A., Schmitz, C., Lotze-Campen, H., Müller, C., and von Lampe, M. (2014). Agriculture and climate change in global scenarios: Why don't the models agree?, *Agric. Econ.*, **45**, 85–101.

Ohrel, S. B., Beach, R. H., Adams, D., Alig, R., Baker, J., Latta, G. S., McCarl, B. A., Rose, S. K., and White, E. (2010). *Model Documentation for the Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG)*, RTI International, RTI Project Number 0210826.016. Available at: http://agecon2.tamu.edu/people/faculty/mccarl-bruce/FASOM.html. Accessed on 15 May 2014.

O'Neill, B. C., Carter, T. R., Ebi, K. L., Edmonds, J., Hallegatte, S., Kemp-Benedict, E., Kriegler, E., Mearns, L., Moss, R., Riahi, K., van Ruijven, B., and van Vuuren, D. (2012). *Meeting Report of the Workshop on The Nature and Use of New Socioeconomic Pathways for Climate Change Research*, Boulder, CO, November 2–4, 2011. Available at: http://www.isp.ucar.edu/socio-economic-pathways. Accessed on 15 May 2014.

Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M., and Fischer, G. (2004). Effects of climate change on global food production under SRES emissions and socio-economic scenarios, *Global Environ. Change*, **14**(1), 53–67.

Rosegrant, M. W., Agcaoili-Sombilla, M., and Perez, N. D. (1995). *Food Projections to 2020: Implications for Investment. Food Agriculture and the Environment Discussion Paper no. 5*, International Food Policy Research Institute, Washington, DC.

Rosegrant, M. W. and the IMPACT Development Team (2012). *International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model Description,* International Food Policy Research Institute (IFPRI), Washington, DC, 2.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Almut, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., and Jones, J.W. (2013a). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison, *Proc. Natl. Acad. Sci.*, **111**(9), 3268–3273.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013b). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Valdivia, R. O. and Antle, J. M. (2012). *DevRAP: A Tool for Designing Representative Agricultural Pathways and Scenarios*. Available at: http://tradeoffs.oregonstate.edu. Accessed on 1 April 2014.

Valdivia, R. O., Antle J. M., and Stoorvogel J. J. (2012). Coupling the Tradeoff Analysis Model with a market equilibrium model to analyze economic and environmental outcomes of agricultural production systems, *Agric. Syst.*, **110**, 17–29.

Van Notten, P. W., Sleegers, A. M., and van Asselt, M. B. (2005). The future shocks: On discontinuity and scenario development, *Technol. Forecast. Soc.,* **72**(2), 175–194.

van Ittersum, M. K., Ewert, F., Heckelei, T., Wery, J., Alkan Olsson, J., Andersen, E., Bezlepkina, I., Brogaard, S., Donatelli, M., Flichman, G., Olsson, L., Rizzoli, A., van der Wal, T., Wien, J. E. , Wolf, J. (2008). Integrated assessment of agricultural systems — A component-based framework for the European Union (SEAMLESS), *Agric. Syst.*, **96**, 150–165.

van Vuuren, D. P., Riahi, K., Moss, R., Edmonds, J., Thomson, A., Nakicenovic, N., Kram, T., Berkhout, F., Swart, R., Janetos, A., Rose, S. K., and Arnell, A. (2012). Scenarios in global environmental assessments: Key characteristics and lessons for future use, *Global Environ. Change*, **22**(1), 21–35.

Van Vuuren, D. P., Kok, M. T., Girod, B., Lucas, P. L., and de Vries, B. (2011). A proposal for a new scenario framework to support research and assessment in different climate research communities, *Global Environ. Change*, **22**(4), 884–895.

Wu, J. J., Adams, R. M., Kling, C. L., and Tanaka, K. (2004). From micro-level decisions to landscape changes: An assessment of agricultural conservation policies, *Am. J. Agric. Econ.*, **86**, 26–41.

Zurek, M. B. and Henrichs, T. (2007). Linking scenarios across geographical scales in international environmental assessments, *Technol. Forecast. Soc.*, **74**(8), 1282–1295.

This page intentionally left blank

Chapter 6

Data Interoperability Tools for Regional Integrated Assessments

Cheryl H. Porter[1], Chris Villalobos[1], Dean Holzworth[2], Roger Nelson[3], Jeffrey W. White[4], Ioannis N. Athanasiadis[5], Meng Zhang[1], Sander Janssen[6], Rob Knapen[6], James W. Jones[1], Kenneth J. Boote[1], John Hargreaves[2], and John M. Antle[7]

[1]*University of Florida, Gainesville, FL, USA*

[2]*Commonwealth Scientific and Industrial Research Organisation, Toowoomba, Australia*

[3]*Washington State University, Pullman, WA, USA*

[4]*United States Department of Agriculture, Agricultural Research Service, Ames, IA, USA*

[5]*Democritus University of Thrace, Xanthi, Greece*

[6]*Alterra, Wageningen UR, the Netherlands*

[7]*Oregon State University, Corvallis, OR, USA*

Introduction

The crop modeling simulations performed as part of the regional integrated assessments (RIA) for AgMIP (Agricultural Model Intercomparison and Improvement Project; Rosenzweig *et al.*, 2013a) involve the use of multiple models, which allows researchers to characterize uncertainty and to facilitate model intercomparisons and improvement. The emphasis on ensemble modeling approaches requires that data used in multi-model simulations be harmonized across models. Common data descriptions for field conditions, management operations, soils characteristics, and weather data must be provided equivalently to each model so that differences in simulated outputs are due to model differences rather than input data differences, as much as possible. This chapter describes the AgMIP approach to achieving data interoperability across multiple crop models, which consists of establishing an efficient standardized data-exchange mechanism with specifications defined in accordance with international standards; implementing a flexibly structured data schema to store experimental datasets; and providing consistent procedures for supplementing model-required inputs (Porter *et al.*, 2014).

The AgMIP RIA crop modeling process begins with collection of data required to parameterize the crop models. Field-management conditions are typically obtained from relatively low-quality data sources such as farm surveys. These data are supplemented with knowledge from regional agronomists regarding typical practices such as cultivars grown and crop-residue management. Soil-profile data are obtained from various sources including the Harmonized World Soils Database (HWSD; FAO/IIASA/ISRIC/ISSCAS/JRC, 2012) and the WISE soil database (Batjes, 2009), complemented with information gained from farm surveys and from knowledge of cropping history. Daily weather data used to drive the models are generated by the AgMIP climate research teams, as detailed in Part 1, Chapter 3 in this volume. The RIA crop modeler transforms these data into fully and correctly parameterized model inputs which describe the management and environmental conditions for the observed farming system using methods described later in this chapter. Model simulations representing these historic or observed conditions are then used to compute model biases.

The historic simulations are used as a basis to extrapolate predictions of crop production for 30 years using: (1) current climate and current management, (2) future climate and current management, and (3) future climate and adapted management. Simulations are performed for multiple climate models, time-periods, emissions scenarios, socio-economic scenarios, and management strategies for climate change adaptation.

Consider a typical case in which an AgMIP regional research team (RRT) is analyzing four regions, each with 150 survey sites over a 30-year time-frame. Suppose historical climate plus four climate change scenarios, generated with five climate models are simulated by using two crop models. This would result in over 750,000 simulations. One must also consider that there will inevitably be procedural mistakes and data corrections requiring multiple re-runs of simulations. Adaptation scenarios and additional crop or climate models add further dimensions to the simulation combinatorics. It is clear that automation is required to facilitate the generation of simulation scenarios, translation of data for multiple crop models, aggregation of outputs, analysis, and visualization of results. This was the motivation for AgMIP to develop a set of standards and protocols for crop model data management and interoperability for RIAs.

Some of the challenges encountered with design of data interoperability protocols involve (1) the use of heterogeneous data from disparate sources, (2) uniformly supplying the required model assumptions where data are insufficient to parameterize the crop models, (3) supplying observed and supplemental data equivalently to multiple models each with different input formats, and (4) harmonizing model outputs for use in further analyses. Figure 1 illustrates these challenges to standardizing AgMIP crop modeling data and streamlining data processing for multiple

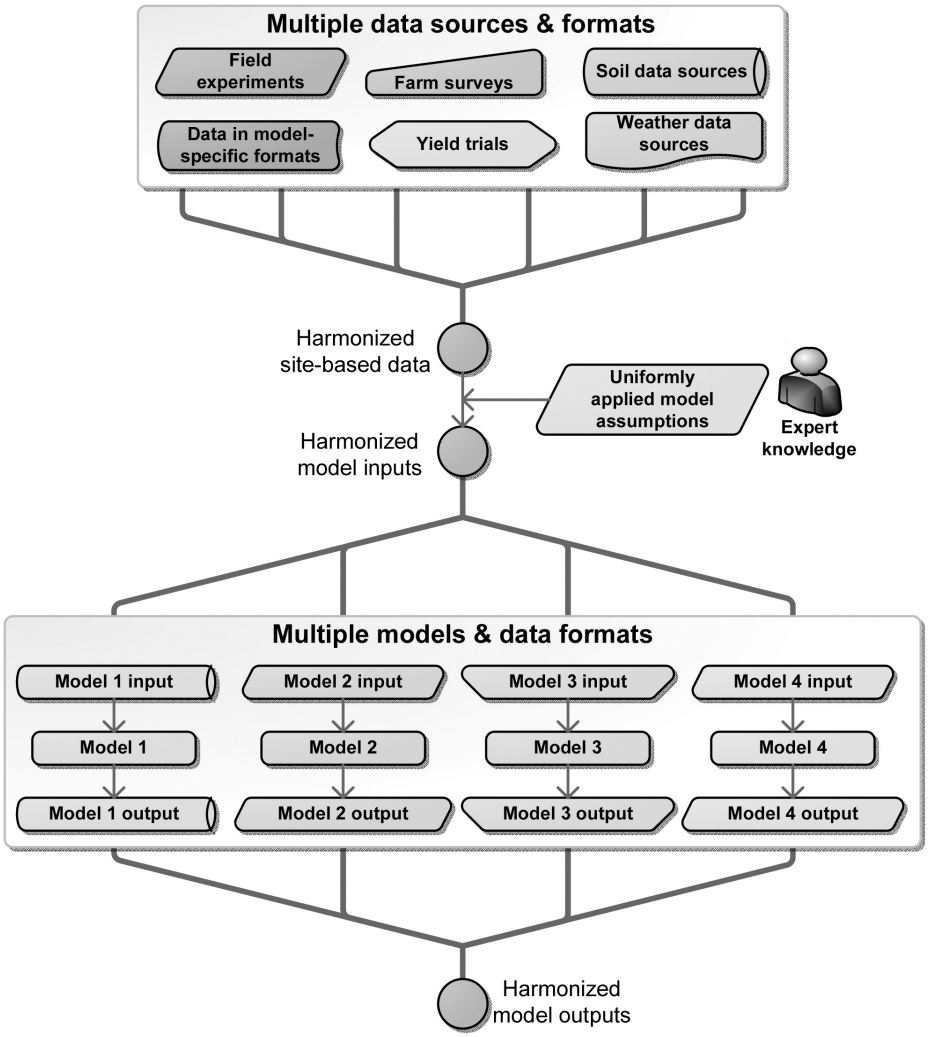


Fig. 1. Data-flow diagram for AgMIP crop modeling activities. Source data, model inputs, and model outputs have diverse and inconsistent formats, hampering ensemble modeling approaches (Porter *et al.*, 2014). Supplemental data and assumptions must be provided equivalently to multiple models. Reprinted from Porter *et al.* (2014), with permission from Elsevier.

models and the mechanisms used to overcome them. Details of the AgMIP data interoperability solution are provided in the next section.

The first challenge deals with inconsistency in the **source data** used in crop modeling. Datasets used to calibrate and validate crop models are obtained from diverse sources and the quantity and quality of the data are influenced by the original purpose of the research, the equipment used for measurement of growth and environmental data, and the methods of analysis used. Field experiments typically

collect detailed records of soil properties, weather conditions, and management practices such as tillage, fertilizer, and water-application dates, rates, methods, and materials. However, farm and household surveys may only collect general information about management practices with only seasonal totals and few details regarding management events. Field studies often record details about crop phenology, canopy, and biomass development and response to management practices, whereas such information is often lacking in surveys. These data sources also vary in storage and schema implementation formats, including databases, spreadsheets, tabular text files, structured XML (extensible markup language), or other specialized formats. Adoption of a common vocabulary and a standard data schema enable AgMIP researchers to overcome these source data incompatibility problems.

The second challenge in AgMIP data harmonization involves the issue of providing a consistent set of **assumptions** for information that is required by models but is not available in the datasets. Even highly detailed field experiments may lack sufficient observations to adequately provide minimum input requirements to the models. For ensemble modeling, it is necessary to harmonize not only the recorded information but also the assumptions used to supply missing model-specific input parameters. This challenge was overcome by development of a system for applying model assumptions to datasets based on the best available information for the region. This system, referred to as the DOME (Data Overlay for Multi-model Export), is discussed below.

The third challenge in data harmonization involves the inconsistent **input data** formats used by crop models. While the various models may implement diverse algorithms, the driving data are generally similar (Boote *et al.*, 2013). Models typically include daily weather records, soil physical and chemical properties, and information related to management practices such as planting, fertilization, irrigation, and harvest. However, the formats in which these data are provided to the models vary widely. This could be a matter of design choice, preference, availability, or even understanding of the underlying phenomena. As an example, soil-data specifications may differ in the soil classification used (sometimes incompatible with each other) and in how vertical differences in a given soil profile are specified (e.g., number and depth of soil layers). A library of model input translators was developed to overcome this challenge.

Likewise, although the core **outputs** from crop models are often similar, the formats are diverse and inconsistent and generally parallel the input-format structure. For example, models running within the Decision Support System for Agrotechnology Transfer (DSSAT; Jones *et al.*, 2003; Hoogenboom *et al.*, 2010) rely heavily on column formatted text for both input and output files, while the Agricultural Production Systems Simulator (APSIM; Holzworth *et al.*, 2013; Keating *et al.*, 2003) relies on XML files, with a semantic heterogeneity on the variable names and

definitions. Model output translators were developed to harmonize the outputs from each participating model.

The key elements of the crop model data interoperability system for AgMIP are a common vocabulary for standardization of definitions and units; a means of harmonizing data collected from disparate sources and which differ considerably in content and quality; a means of providing datasets in the model-ready formats required by multiple models; and a means of harmonizing simulated model outputs. Harmonized datasets must be searchable with source data and model outputs linked in such a way that model results can be documented and replicated.

AgMIP Data Interoperability Solution

AgMIP crop experiment (ACE) harmonized data schema

The AgMIP crop experiment (ACE) harmonized format was designed to provide a means of storing the highly variable types of data associated with AgMIP crop modeling exercises in a flexible and efficient schema. The ACE data format relies on a common vocabulary that is independent of the structure and level of detail provided by the data sources. The standards developed by the International Benchmark Sites Network for Agrotechnology Transfer Project (IBSNAT, ICRISAT, 1984; Uehara and Tsuji, 1998) and subsequently revised by the International Consortium for Agricultural Systems Applications (ICASA) were designed to provide a comprehensive means of describing field experiments with the goal of facilitating exchange of agricultural information (Hunt *et al.*, 2001; White *et al.*, 2013).

The foundation of the ICASA standards is the Master Variables List (ICASA-MVL, see http://research.agmip.org/display/it/Data+Interoperability). This data dictionary is organized in a hierarchical structure with four major divisions: management practices, soil characteristics, weather, and measurements of crop and soil responses. The ICASA-MVL was selected as the foundation of the ACE data definitions because of its comprehensive and detailed descriptions of management practices and traits of soils and plants for crop experiments. The list is flexible and extensible, which allows AgMIP researchers to modify and improve the list as needed for AgMIP modeling activities. These changes included defining model variables that were not previously described, clarifying definitions that could have distinct interpretation in different models, and accommodating metadata specifically required for AgMIP purposes.

AgMIP site-based agricultural datasets have a wide range of quality and quantity of records collected depending on the data sources, and therefore these data do not easily conform to a rigid schema. A flexible, non-relational database architecture was selected to accommodate the diverse data structures and contents encountered.

Data are organized in ACE using type-agnostic JSON (JavaScript object notation, www.json.org) key-value structures. These key-value structures store all data in <attribute name, value> pairs. This allows the storage of information for both simple observations and complex structured objects in an efficient, consistent and open-ended format. The key (attribute name) in each pair corresponds to an ICASA-MVL variable; the value conforms to the variable definition, including units.

The core structure of ACE divides model data into three compartments that reflect the common drivers in most models, i.e., (a) experimental management, (b) soil characteristics, and (c) weather-related information. Each compartment is assigned an identification key, or hash code (NIST, 2012), generated from the contents. Weather and soil structures are associated with experimental site data via these identification keys. This allows imposition of one-to-many relations between experimental data and soils or weather data.

An important feature of ACE data is that there are no minimum data other than location (latitude and longitude) and crop species. All other data are optional and the data structure will contain key-value pairs for only the data collected in the survey or experiment. This provides a convenient and efficient data-storage structure.

Figure 2 presents two sample JSON fragments for an AgMIP dataset which includes four soil nodes (numbered 0–3), five experiment nodes, and four weather nodes. In Fig. 2a, the second field-experiment data node is expanded to show field geolocation, metadata, and the initial field conditions and management substructures. The "fl_lat" key corresponds to the ICASA variable defining field latitude as 37.75°S. One of the three management event substructures is expanded to show a fertilizer event with 120 kg/ha urea added (keys "feamn" and "fecd"), broadcast and incorporated to a depth of 5 cm (keys "feacd" and "fedep"). Figure 2b shows an expansion of the data in one of the soil-data structures, including one of seven soil layers. The key "sloc", for example, corresponds to a soil organic-carbon value of 0.31%. The soil for the experiment site, identified by "WP_ARG1234" (highlighted in Fig. 2a), is associated with the soil definition in the experiment data (shown in Fig. 2b) via the "soil_id" key field.

Data Overlay for Multi-model Export (DOME)

DOME provides a mechanism for users to provide model-specific assumptions and has several potential uses for model intercomparison. First, this feature allows researchers to provide supplemental information in order to utilize incomplete datasets. Missing parameters that are required by models can be supplied through one or more DOMEs which allow researchers to make assumptions uniformly based on the best agronomic knowledge of cultural practices in a region. These supplemental data are applied as an overlay, which allows the assumed information to remain

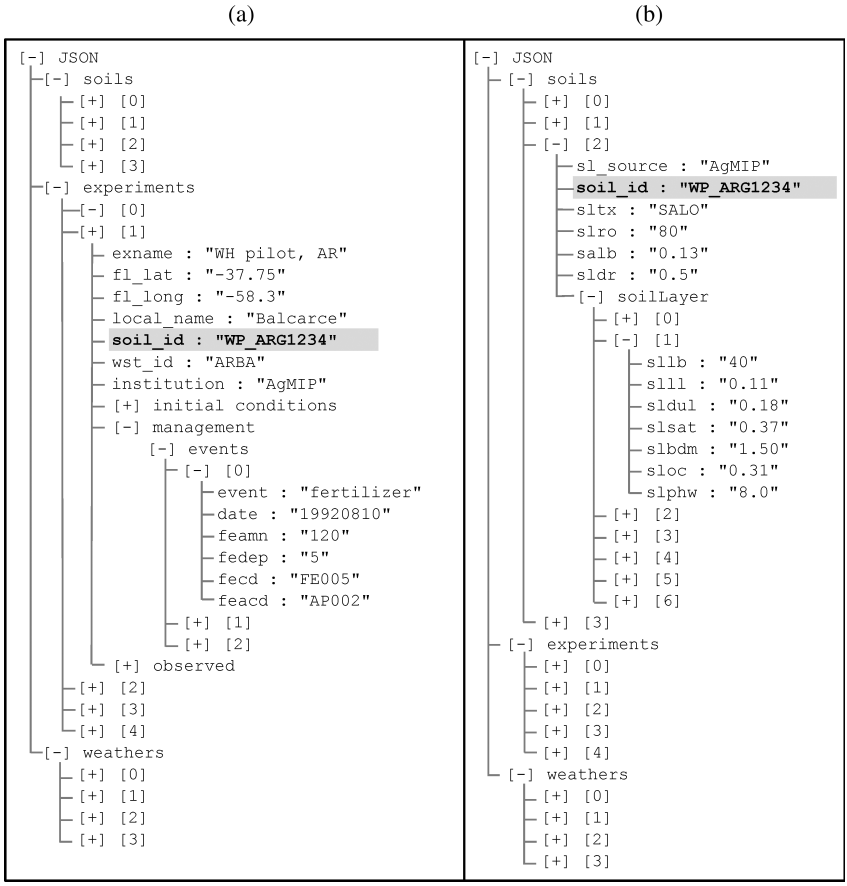


Fig. 2. Fragment of ACE JSON structure showing (a) expanded experiment data and (b) expanded soil data. The highlighted soil identifiers show how a specific soil profile is linked to an experiment.

separate from field-measured observations and ensures that all models are provided with a consistent set of assumptions. A DOME which is specifically used to provide a complete dataset for crop model simulations is referred to as a "*field overlay*".

In addition to filling in missing information, DOMEs can be used to impose hypothetical management regimens, in order to simulate adaptation or other "what-if" scenarios. A "seasonal strategy" DOME allows a researcher to replicate management rules over multiple years for existing or climate change scenarios. The DOME associates metadata that describes the climate scenario, including global climate model, downscaling method, and represented historical or future time-slice, as well as identification of any adaptation strategies imposed. These metadata are an important component of maintaining a record of data provenance in the regional integrated assessment modeling process.

Table 1. Partial listing of DOME functions used to supply missing information to crop models or to impose hypothetical management regimens.

DOME function	Description
OFFSET	Add or subtract a number from the specified variable
OFFSET_DATE, DATE_OFFSET	Add or subtract a number of days from a specified date variable
MULTIPLY	Multiply the specified variable by a factor
PCTAWC	Compute water content in each soil layer from the specified percent available water
ICN_DIST	Initial soil nitrogen distribution function
AUTO_PDATE	Automatic planting date function
FERT_DIST	Fertilizer distribution function
OM_DIST	Organic matter application details
ROOT_DIST	Root distribution function
STABLEC	Stable soil carbon distribution
InitSW_dist	Initial soil water distribution
TAVAMP	Temperature average annual and amplitude
PADDY	Rice-paddy management function
AUTO_REPLICATE_EVENTS	Clones management events over multiple years
LYRSET	Soil-layer splitting function
AUTO_IDATE	Automatic irrigation date function
TRANSPOSE	Insert array value (e.g., for soil-layer data)

"Rotational strategy" DOMEs can be used to simulate long-term, continuous crop rotations. Like seasonal strategy analyses, the climate scenario and management regimen can represent historical, baseline, or hypothetical future conditions. Unlike seasonal strategy analyses, soil properties such as water and nitrogen content are initialized only once at the beginning of the continuous simulation period, rather than at the beginning of each planting season.

DOMEs operate through the specification of functions, which compute model inputs based on other available data. Table 1 presents a partial listing of DOME functions that were available as of this publication. All DOME functions are fully documented on the AgMIP research site (see http://research.agmip.org/display/it/Data+Interoperability).

Model-specific parameters that are not included in the ICASA-MVL can be supplied in a DOME, provided that the model translator is equipped to interpret the values. The DOME concept contributes to the vision of domain-specific languages for environmental modeling (Athanasiadis and Villa, 2013) by defining a set of domain-specific data operands for supplying missing information to crop models.

AgMIP crop model output (ACMO)

Simulated outputs from the crop models are harmonized and archived in the ACMO format to be used for further analysis, aggregation, and input to economic models. As with ACE, the ACMO schema conforms to the ICASA-MVL. Unlike ACE, the ACMO data are uniform, with each dataset containing exactly the same elements. Crop and economic modelers collaborated in the design to ensure that ACMO data are sufficient for use in the economic models, yet readily available from the outputs of most crop models. A full list of ACMO variables are listed and defined on the AgMIP research site (http://research.agmip.org/display/it/Data+Interoperability). Because of the consistent content of metadata and simulated outputs, regardless of model or simulation scenario, ACMO data are stored in a tabular text format.

Data translation libraries

Three types of translation tools were developed to support AgMIP crop modeling activities: (1) ACE input translators, which allow data to be imported from various formats into the ACE harmonization, (2) ACE output translators, which take combined ACE and DOME data and generate crop model ready files for crop simulation models, and (3) ACMO translators, which convert crop model outputs into a harmonized format. In most cases, these programs were developed as libraries of translation tools which can be implemented in multiple ways, including desktop applications, web services, and parallel-processing platforms for large-scale modeling applications. Table 2 lists the status of ACE input, ACE output, and ACMO translators completed or in development. The AgMIP regional research teams use the desktop applications discussed herein for use in regional integrated assessments crop modeling analyses.

ACE input translators: Input translators facilitate conversion of raw data from a variety of formats including spreadsheet templates encoded with ICASA variable names. Several spreadsheet templates have been provided to AgMIP users to accommodate differing levels of detail and widely varying management options, including templates for farm survey data, rice-paddy management systems, fertilizer trials, breeder trials, detailed crop experiments, and other options. The primary formatting requirement is that the data elements entered into a spreadsheet must be identified with an ICASA variable name and must conform to units specified in the ICASA-MVL. Examples of these spreadsheet templates are provided in the supplemental data at http://research.agmip.org/display/it/Data+Interoperability.

Model-specific input translators have been developed to import model data directly from the input files for some of the models actively used in AgMIP research. As of this publication, only the DSSAT and CropGrow-NAU ACE input translators

Table 2. Status of translator development for 13 participating models (Porter *et al*., 2014). Translators are labeled "operational" if they have been implemented in translation applications; "nearing completion" if a team is actively working to finalize the translator; "under development" if work has begun, but is not yet complete; and "—" indicates that translator development has not begun. Reprinted from Poster *et al.* (2014), with permission from Elsevier.

Crop model	ACE input translator status	ACE output translator status	ACMO translator status	Reference for crop model
APSIM	Under development	Operational	Operational	Holzworth *et al.*, 2013; Keating *et al.*, 2003
AquaCrop	—	Nearing completion	Under development	Hsiao *et al.*, 2009; Raes *et al.*, 2009; Steduto *et al.*, 2009
CropGrow-NAU	Operational	Operational	—	Zhu *et al.*, 2004
CropSyst	Under development	Operational	Operational	Stöckle, *et al.*, 2003
DSSAT	Operational	Operational	Operational	Hoogenboom *et al.*, 2010; Jones *et al.*, 2003
EPIC	—	Under development	—	Izaurralde *et al.*, 2006
InfoCrop	—	Under development	—	Aggarwal *et al.*, 2006
ORYZA2000	—	Under development	—	Bouman and Van Laar, 2006; Bouman *et al.*, 2001
RZWQM2	—	Under development	—	Ahuja *et al.*, 2000
SALUS	—	Operational	—	Basso and Ritchie, 2012; Basso *et al.*, 2010
SarraH	—	Under development	—	Sultan *et al.*, 2013; Oettli *et al.*, 2011
STICS	Under development	Operational	Operational	Brisson *et al.*, 2009; Brisson *et al.*, 2003
WOFOST	—	Operational	Operational	Van Diepen *et al.*, 1989

were operational. Additional translators for APSIM, CropSyst, and STICS are currently under development. These model-specific input translators will allow many existing datasets associated with each modeling platform to be harmonized and made available to AgMIP researchers, in the formats specific to each model.

The AgMIP climate team developed a standard format file for disseminating daily weather records, as described in the AgMIP protocols (Rosenzweig *et al.*, 2011). Translators to convert these weather files to the ACE harmonized format were the first AgMIP input translators to be developed.

ACE output translators: Translators that convert data from the harmonized ACE format to model-ready formats were written for 13 models at the time of this publication (see Table 2). Five of the translators (APSIM, CropGrow-NAU, DSSAT, STICS, WOFOST) are used in a desktop translation utility and are currently available for use by AgMIP researchers. Additionally, the CropGrow-NAU, CropSyst, and EPIC models have translators linked to their respective model or user interfaces, which thus allows these models to use the ACE data format directly. Other ACE output translators are in various stages of development and will be available for future AgMIP modeling activities.

ACMO translators: ACMO translators are also currently available to AgMIP researchers for the APSIM, CropGrow-NAU, CropSyst, DSSAT, and WOFOST models. Translators for other participating models listed in Table 2, are being developed. The ACMO harmonized data include all metadata that describe the simulation, including links to the ACE and DOME data used in the simulation. These metadata are typically not available from the outputs of crop model simulations and so the ACMO file is partially created at the time of ACE data translation to crop model formats. After crop model simulations are complete, the ACMO translators combine the metadata with the simulated outputs into the ACMO harmonized file, in comma-delimited (csv) format.

Data provenance

Reproducibility and integrity of archived data is extremely important for AgMIP researchers. The data resulting from each analysis must include information related to the sources as well as to all intermediate modifications. The metadata included with ACE, DOME, and ACMO data enforce these provenance requirements. Metadata for each ACE dataset may include the source of field, weather, and soils records, the names and institutions of researchers involved in the collection of data, and location of measurements. DOME metadata include identification of the management regimen, adaptation scenario, and climate scenarios. Simulated model outputs in the ACMO file are connected via metadata to the raw data collected by researchers; the transformations and additions supplied by DOMEs; and the model name and version used for each simulation. The metadata fully identify the modeled scenario and provide the identification of simulated model outputs with the ACE datasets and DOMEs used to generate the model inputs.

Archived ACE, DOME, and ACMO datasets are tagged with hash codes which are generated from the data contents at the time of translation to harmonized format. This allows verification of the data integrity at every step in the processing chain. Hash codes are used to link the ACMO simulation outputs to the ACE and DOME data used to drive the simulation. When an existing archived ACE dataset is modified

in a way that would affect simulated outputs for one or more models, a new unique hash code is generated and the new dataset is stored, linked to the original. In this way, a history of modifications can be maintained. Modified datasets are available to users, but a warning message is issued that the data may have been superseded.

Implementation of AgMIP Data Interoperability Tools

Desktop applications

All desktop data-translation applications described herein are available for download from the AgMIP toolshed at tools.agmip.org. These tools have been used to generate model inputs for ensemble modeling exercises for AgMIP regional integrated assessments, model intercomparison projects, and other crop modeling activities. All AgMIP software products, including the data translators and the desktop applications, have been developed as open-source projects and are available for download or contribution from github.com/agmip.

QuadUI

ACE input and output translators are bundled with the DOME interpreter in the QuadUI desktop application (see Fig. 3). The utility reads user-specified, site-based crop modeling data from one of several different formats and translates these data into model-ready input files for multiple models. QuadUI combines ACE and DOME data into a single JSON data-stream, which is supplied to the selected model-specific ACE output translators.

ACE data to be translated to crop model formats are provided by the user in a zip-format archive file containing one or more csv-format files containing the survey, soils, and weather data. These data were previously prepared using the standard data templates for ACE input translators, or other acceptable data input formats as described previously. Optionally, one or more field overlay DOME files can be provided in a single zip-format archive file. Seasonal strategy DOMEs, also optional, can be bundled together and specified by a user for generating multi-season simulations. Rotational strategies have not yet been implemented in QuadUI.

Model-ready files are written to a directory selected by the user, with separate sub-directories created for each crop model selected. A metadata file is also created at the time of translation for use in later generation of the ACMO files. QuadUI also generates compressed JSON files for ACE and DOME data. These compressed ace-binary files are the format that can be uploaded to an online AgMIP database.

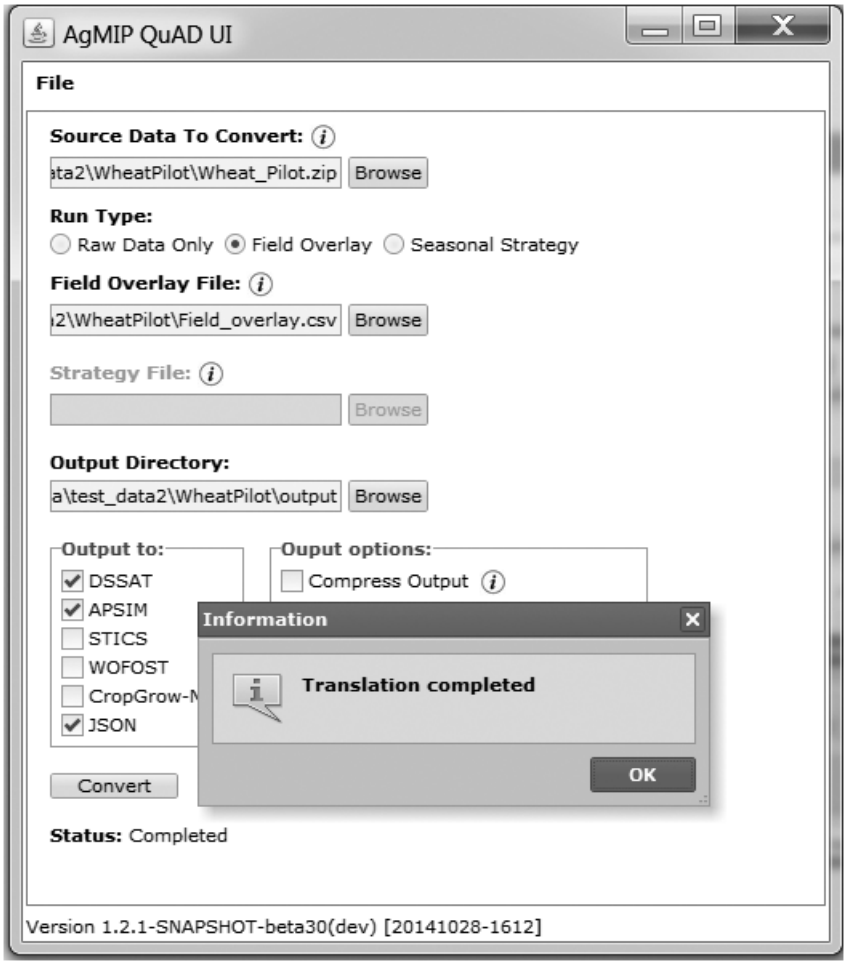


Fig. 3. QuadUI desktop application for conversion of raw data to model-ready formats. Users select the data file and optionally one or more DOME files. Data are converted into harmonized format and to one or more model-specific formats.

ADA

Raw data from surveys or field experiments are often entered into spreadsheets to facilitate data entry, conversion of units, and organization of data. The AgMIP Data Assistant (ADA, Fig. 4) desktop application exports multiple worksheets in a Microsoft Excel spreadsheet to csv format. Each worksheet is written to a separate csv file and the files are compressed in zip format.

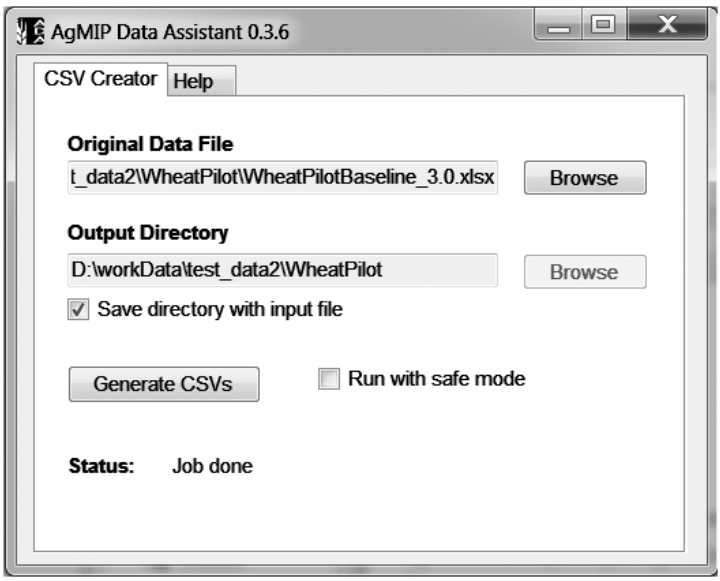


Fig. 4. ADA desktop application exports Excel worksheets to csv format in preparation for input to QuadUI.

ACMOUI

The ACMOUI application, shown in Fig. 5, is a separate desktop utility for harmonizing crop model outputs from multiple models. The model-specific ACMO translators append simulated outputs from the selected crop model to the metadata file generated by QuadUI. ACMO file names are generated from metadata and are of the form: "ACMO-Region-Stratum-Climate_ID-RAP_ID-Management_ID-Crop_model.csv". For example, an ACMO file from a DSSAT simulation of conditions in the Machakos region of Kenya for current climatology might result in a file name of "ACMO-Machakos-1-0XFX-0-0-DSSAT.csv", where OXFX is the climate identification for 1980–2010 baseline climatology using 2.5 minute WorldClim data and historical observations (see climate scenario naming conventions in Appendix 1, Part 1 in this volume).

AgMIP data interchange

The AgMIP Data Interchange (data.agmip.org) is the portal for accessing data relevant to AgMIP researchers. As of this publication, the site provides access to site-based datasets used in crop modeling activities in the AgMIP crop site database. These data include survey data associated with the RIAs, field research experimental data, and yield trial data from private industry and research institutions. These data include not only the field-observed data (ACE data), but also DOME (model

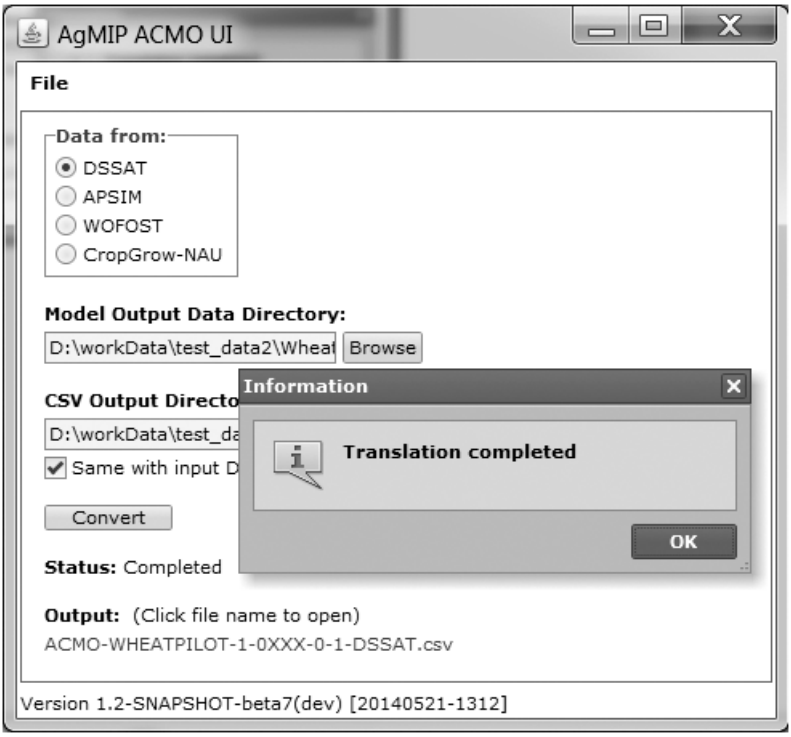


Fig. 5. ACMOUI converts simulated outputs from multiple crop models to harmonized ACMO format.

assumptions and scenarios) and ACMO data (simulated outputs) from crop modeling exercises. Data are uploaded, stored, and downloaded in the AgMIP harmonized data formats. Data translation utilities (QuadUI and ACMOUI) are used to generate the ACE- and ACMO-formatted data for upload to the site. Datasets that are downloaded from the site can be processed through QuadUI to generate crop model ready input files.

AgMIP protocols advocate open data policies and the intent of the AgMIP Data Interchange is to make these datasets freely available to anyone who wishes to use them. It is also recognized that researchers may wish to withhold publication of some datasets until their research results have been published. Some data used in AgMIP activities are not in the public domain, particularly historical weather observations which may be considered intellectual property by the entities that collected the data. For this reason, the AgMIP crop site database has three levels of data accessibility: (1) datasets which are freely available under the Creative Commons Attribution license (see creativecommons.org/licenses/by/3.0/us); (2) datasets that have been uploaded to the database, but that are restricted from download for a specified

period of time before they are made available under the same Creative Commons Attribution license; and (3) datasets that are permanently restricted from download due to intellectual property issues. In the third case, only the metadata describing the data are stored in the AgMIP Data Interchange. Users who request these data are directed to the owner. Open datasets are available for download to anyone accessing the AgMIP Data Interchange; however only registered users have permission to upload data to the site.

The databases for ACE, DOME, and ACMO were designed using a Riak platform (basho.com/riak). Riak is an open-source, distributed database designed for scalable, fault-tolerant operation. The AgMIP implementation consists of multiple data nodes at facilities involved with AgMIP activities. As of this publication, the first data node was in testing phase at the University of Florida, with future nodes planned for University of Passo Fundo, Brazil; the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), India; and other locations.

AgMIP researchers are active in many countries and regions around the world. The data that are served by AgMIP must be made readily available in a format that can be searched and accessed efficiently by researchers who may lack access to high-speed internet connections. Many ensemble modeling approaches use 30 years or more of daily weather data associated with each climate scenario, climate model, downscaling method, and time-slice. Thus, weather datasets required for regional integrated assessments can be large. All data are uploaded and downloaded from the server use a compressed format (ace-binary) to minimize transfer latency.

In the future, additional data linkages to the AgMIP Data Interchange will allow access to climate datasets, soils databases, socio-economic model input and output data, and raster data relevant to gridded crop modeling applications.

Open Data Journal for Agricultural Research

AgMIP, in collaboration with MACSUR, Global Yield Gap Atlas, CIMSANS, and Wageningen UR, is developing a data journal for publishing peer-reviewed datasets associated with agricultural research. The *Open Data Journal for Agriculture Research* (*ODjAR*) will act as a central hub for storing, curating, and publishing the datasets as a resource for the future where publications and their authors get appropriate credit through citations and digital object identifiers for future reference. This valuable resource will allow datasets to be made available to researchers after a funding period ends and the research is published.

Next-generation AgMIP tools

The first-generation desktop utilities, QuadUI and ACMOUI, currently used in AgMIP RIAs, were developed quickly in response to an immediate need by RRTs.

It is recognized that the iterative process for generating and manipulating ACE and DOME data to produce successful and accurate simulations with multiple models, can be a cumbersome process. The list of variables in the ICASA-MVL is extensive and can be overwhelming for a user who is not familiar with the terms and structure of the data definitions. The format of the DOME is essentially a domain-specific language (DSL), which is often difficult for researchers to learn. For these reasons and others, we recognize that the next-generation user interfaces must facilitate data entry, manipulation and translation in framework that is easier to use.

The AgMIP IT team has begun conceptual design of an enhanced desktop utility for data handling that will combine the capabilities of QuadUI, ACMOUI, and the web interface for the AgMIP Data Interchange. Researchers will use this multi-function application for direct input of ACE and DOME data and to perform the process of refining the inputs to generate useful and accurate simulations. Models which can be run with a command line will be accessed directly from the interface, with ACMO outputs generated automatically. Direct linkage to the server will allow a user to search the database, download datasets, manipulate the data, and upload results to the server, all within a single desktop application.

Under a National Science Foundation project called Framework to Advance Climate, Economic and Impact Investigations with Information Technology (FACE-IT, www.faceit-portal.org), researchers are developing a web-based, interactive platform to support modeling activities for AgMIP and other research groups. This platform will allow a user to create complex workflows within a visual interface; connect the workflow to diverse data sources; visualize the data; and share the workflow, data, and outputs with other researchers conducting similar types of research. The platform uses the Galaxy workflow engine, used extensively in data-intensive biology applications, but under modification for use in earth science domains. For this NSF project, the AgMIP RIA process represents a use case. Workflow applications within the FACE-IT toolshed include the DSSAT and APSIM biophysical models; data translation utilities developed for AgMIP; climate data manipulation algorithms used by AgMIP climate scientists; and data visualization applications developed for FACE-IT. It is envisioned that this platform will facilitate ensemble modeling efforts for researchers worldwide as it moves into an operational phase in 2015.

Use of Data Translation Tools in the RIA Process

The AgMIP regional research teams in South Asia and Sub-Saharan Africa use AgMIP protocols to conduct regional integrated assessments to quantify the effects of climate change on food security in their regions. The teams use multiple climate,

crop, and economic models to answer three key core questions:

1. What is the sensitivity of current agricultural production systems to climate change?
2. What is the impact of climate change on future agricultural production systems?
3. What are the benefits of climate change adaptations?

The AgMIP regional integrated assessment process requires collaboration among a multi-disciplinary team to provide consistent and cohesive inputs at each phase of the process for climate, crop, and economic analyses. These processes are described in detail in the AgMIP Regional Integrated Assessment Handbook (see Appendix 1, Part 1 in this volume) and throughout this volume. This use case focuses only on the crop modeling process, which uses outputs of climate models as input and which generates inputs for the economic modeling phase of the assessments. A simplified data-flow diagram for the crop modeling process is shown in Fig. 6, which shows the use of the three types of data translators and the two desktop utilities, QuadUI and ACMOUI.

Many sets of crop modeling simulations are required in order to evaluate current climate and technology conditions, future climate conditions with current technology trends and future climate conditions with adaptation. Future systems are simulated for multiple climate models, climate scenarios, and time-slices; using multiple crop models; and multiple site years. This results in hundreds of thousands of simulations which are to be evaluated and compared and used as input to regional economic models. The processes described below are for analysis of the historical conditions represented by the collected survey data. The data-translation process for analyses of seasonal strategies and future climate and adaptation scenarios is similar, but includes the application of additional seasonal strategy DOMEs.

The use of translation tools in the regional integrated assessments is part of an iterative process. The site-based data are collected, converted into the correct format and units as specified in the ICASA-MVL, and input to a survey data template, typically in a spreadsheet. The templates are modified by the crop modelers to include the appropriate ICASA variables associated with the available survey data for each regional analysis. Data are entered on separate worksheets for field and management data, soil data, and for each weather station.

A field overlay DOME is created using a spreadsheet template to supply data required by the crop models, but not provided in the farm or household survey data. DOME templates are available for users to modify with their site- and region-specific crop model inputs. Multiple DOMEs may be necessary to apply selective parameters to different soil types or socio-economic strata or to impose spatial variability among sites in an assessment.

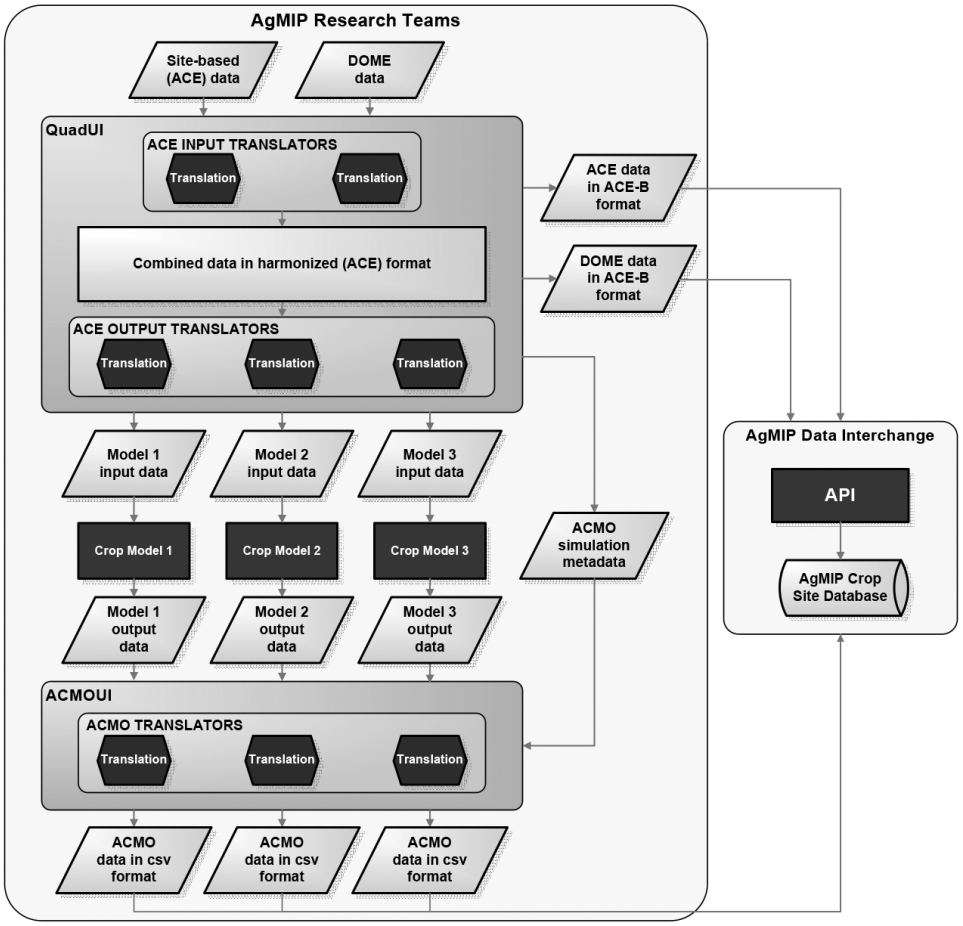


Fig. 6. Crop modeling data-flow diagram for AgMIP RIAs showing ACE input, ACE output, and ACMO translators as implemented in desktop utilities QuadUI and ACMOUI (Porter *et al.*, 2014). Reprinted from Porter *et al.* (2014), with permission from Elsevier.

ACE and DOME data are converted from spreadsheet format into csv format, then converted into a compressed zip format, either manually or using the AgMIP data assistant (ADA) desktop utility.

Generation of ACE and DOME data that produce error-free simulations for multiple models and multiple sites is an iterative process. QuadUI is used to read the survey and DOME data from the zipped archives, combine them into a single data stream, and translate into user-selected model formats. Syntax errors, misspelling of key variable names or DOME functions, or omission of critical information can all cause the translation to fail. When translations occur without error, the models may still fail if required model inputs are omitted. The models may run without error but produce results that do not adequately describe actual regional yields or

other observed data. At each stage, the user must troubleshoot the problems using the QuadUI log, model outputs, and error messages, and by revising the survey and DOME sheets as needed to correct problems.

Once the simulations for historical conditions are successful, ACMOUI is used to generate the ACMO harmonized model output data for each analysis and each crop model. These data are then available in csv format for use by the regional economic models.

At the time that data are translated to model-ready formats, QuadUI generates a file that contains metadata for the simulation. This ACMO_meta.dat file is read by ACMOUI and combined with the simulated crop model outputs to generate the final ACMO file for each simulation. Thus, the final product from the process, the ACMO file, contains sufficient information regarding the scenario modeled to allow a researcher to recreate the simulations.

Analyses of multi-season systems for current and future climate conditions and adaptation scenarios follow the same process, and use the same field-overlay DOMEs. Seasonal strategy DOMEs are applied to impose automatic planting date rules, future management regimens, and to simulate over 30 weather years (current or future).

The final step in the process is for the user to upload the ACE, DOME, and ACMO data to the AgMIP crop site database using the AgMIP Data Interchange web interface (data.agmip.org/). ACE and DOME files are uploaded in compressed ACE (ace-binary) format; ACMO files are uploaded in csv format.

Discussion and Conclusions

The AgMIP harmonized data solution was developed in response to a need by the AgMIP community of researchers for interoperability of data for multiple crop models for assessment of climate change on food security. The ACE harmonized data format provides a simple, flexible, and extensible means of handling site-based agricultural data from diverse sources and for making them available as input to multiple crop models. The design of the data structures and modifications to the underlying ICASA data dictionary were collaborative efforts between the 13 crop modeling groups that participated in AgMIP Software Development Sprints in 2012 and 2013 (see research.agmip.org/display/itwiki/AgMIP+Development+Sprints) and the economists who will use outputs from the crop models.

The key-value schema of the ACE harmonized data format provides an efficient and flexible means of defining and archiving the irregular site-specific data from diverse sources. The DOME provides a means for users to supply information such as assumed management details, initial conditions, simulation time-span, or hypothetical management regimens, consistently and transparently, to multiple

models. Harmonization of simulated model outputs facilitates consistent analysis and interoperability of the results from multiple models and makes the data more readily available for input to economic models.

The expertise of the modeler is critical in the RIA process. The tools and data provide only the input files for running the model, after which the modeler must step in, and check for missing values, out-of-bounds parameters, syntax errors, or inaccurate inputs, then correct these through iterative passes of DOME inputs. The modeler remains responsible for calibrating the model, validating the outputs, and generating appropriate scenarios for different climate, technology, or variety specifications. This focus on the practices of the modeler has an important implication in that the tools must be flexible enough to handle both the data used in the experiment and the model running the experimental data. This flexibility comes at a cost because for each combination of an experimental dataset and a modeling tool, an intervention of the modeler is required to fill parameters and to validate the model, including considering whether a given experiment can be run with a given model, and which experimental data can be adequately included. For example, it does not make sense to run an experimental dataset with detailed observations of nutrient dynamics through a crop model that lacks modules to compute nutrient dynamics.

The current implementation of AgMIP data interoperability tools uses spreadsheet templates and desktop utilities to allow researchers to harmonize and translate site-based data. These tools filled an immediate need for the researchers but remain difficult to use. Next-generation tools will include more interactive user interfaces and web-based approaches. The existing data schemas and translators are sufficiently flexible to be implemented in next-generation utilities without redesign.

The AgMIP data management system was designed to address the needs of a large, distributed, multi-model research community by adopting a rich, extensible vocabulary to describe site-based agricultural data from diverse sources; flexible data structures that allow both detailed and lesser-quality records to be stored in an efficient database; and the ability to provide a consistent set of assumptions and parameters which can be extrapolated to multiple models. For the first time ever, researchers and modelers are able to use these tools to run an ensemble of models on a single, harmonized dataset. This allows them to compare models, leading ultimately to model improvements.

Perhaps the most important outcome is that the AgMIP project has provided a platform that facilitates researcher collaboration from many organizations, across many countries. The level of cooperation between these groups is unprecedented and has already resulted in data interoperability tools that will benefit the large crop modeling community of researchers by making data from a wide variety of sources available to any model user. This would have been very difficult to achieve without the AgMIP data standards described in this chapter. As AgMIP grows to include

more regions, researchers, and modeling groups, the harmonized data format and translation tools will continue to be valuable resources.

Acknowledgements

The authors acknowledge the efforts of numerous model experts and software developers who participated in code sprints and otherwise contributed to developing, testing, and implementing ACE, DOME, and ACMO data schemas. These contributors are listed in the following table.

Crop model	Translator developers
APSIM	D. Holzworth (CSIRO, Australia), I. Athanasiadis (Democritus University of Thrace, Greece)
AquaCrop	D. Raes (KU Leuven University, Belgium), R. Knapen (Alterra WUR, the Netherlands)
CropGrow-NAU	Z. Yan, L. Liu, X. Qiu (Nanjing Agricultural University, China)
CropSyst	R. Nelson (Washington State University, USA)
DSSAT	C. Porter, M. Zhang (University of Florida, USA)
EPIC	R. Sahajpal (University of Maryland, USA)
InfoCrop	N. Kalra (Tata Chemicals, India), S. Pamuru (Concat Systems, Inc., USA)
ORYZA2000	E. Manalo (International Rice Research Institute, Philippines), B. Sailaja (Directorate of Rice Research, India)
RZWQM2	P. Bartling (USDA ARS, USA)
SALUS	B. Baer (Michigan State University, USA)
SarraH	H. Songoti (Agrhymet, Niger), M. Zhang (University of Florida, USA)
STICS	D. Ripoche, J. Cufi (INRA, France)
WOFOST	J. teRoller, D. van Kraalingen, S. Janssen (Alterra WUR, the Netherlands)

We also recognize the larger AgMIP community including the members of the AgMIP regional research teams in South Asia and Sub-Saharan Africa, whose suggestions guided the development of the software products. Much of the support for development of the ACE data format, the data translation tools and the desktop and web-based user interfaces was provided under a grant by the UK Department for International Development (DFID).

References

Aggarwal, P. K., Kalra, N., Chander, S., and Pathak, H. (2006). InfoCrop: A dynamic simulation model for the assessment of crop yields, losses due to pests, and environmental impact of agro-ecosystems in tropical environments. I. Model description, *Agric. Syst.*, **89**(1), 1–25.

Ahuja, L. R., Rojas, K. W., Hanson, J. D., Shaffer, M. J., and Ma, L. (eds.) (2000). *The Root Zone Water Quality Model*, Water Resources Publications LLC, Highlands Ranch, CO, p. 372.

Athanasiadis, I. N. and Villa, F. (2013). A roadmap to domain specific programming languages for environmental modeling: Key requirements and concepts, *Proc. DSM-13*, ACM, pp. 27–32.

Basso, B., Cammarano, D., Troccoli, A., Chen, D., and Ritchie, J. T. (2010). Long-term wheat response to nitrogen in a rainfed Mediterranean environment: Field data and simulation analysis, *Eur. J. Agron.*, **33**, 132–138.

Basso, B. and Ritchie, J. T. (2012). Assessing the impact of management strategies on water use efficiency using soil-plant-atmosphere models, *Vadose Zone J.*, **11**(3).

Batjes, N. H. (2009). Harmonized soil profile data for applications at global and continental scales: Updates to the WISE database, *Soil Use Manage.*, **25**, 124–127.

Boote, K. J., Jones, J. W., White, J. W., Asseng, S., and Lizaso, J. I. (2013). Putting mechanisms into crop production models, *Plant, Cell, Environ.*, **36**, 1658–1672.

Bouman, B. A. M., Kropff, M. J., Tuong, T. P., Wopereis, M. C. S., Ten Berge, H. F. M., and Van Laar, H. H. (2001). *ORYZA2000: modeling lowland rice*, International Rice Research Institute, Los Baños, Philippines, and Wageningen University and Research Centre, Wageningen, the Netherlands, p. 235.

Bouman, B. A. M. and Van Laar, H. H. (2006). Description and evaluation of the rice growth model ORYZA2000 under nitrogen-limited conditions, *Agric. Syst.*, **87**, 249–273.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussiere, F., Cabidoche, Y. M., Cellier, P., Debaeke, P., Gaudillere, J. P., Henault, C., Maraux, F., Seguin, B., and Sinoquet, H. (2003). An overview of the crop model STICS, *Eur. J. Agron.*, **18**, 309–332.

Brisson, N., Launay, M., Mary, B., and Beaudoin, N. (2009), *Conceptual basis, formalisations and parameterization of the STICS crop model*, Editions QUAE, Versailles, France.

FAO/IIASA/ISRIC/ISSCAS/JRC (2012). *Harmonized World Soil Database (Version 1.2)*, FAO, Rome, Italy and IIASA, Laxenburg, Austria. Available at: http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/. Accessed on 7 March 2014.

Holzworth, D., Huth, N., deVoil, P., Zurcher, E., Herrmann, N., McLean, G., Chenu, K., van Oosterom, E., Snow, V., Murphy, C., Moore, A., Brown, H., Whish, J., Verrall, S., Fainges, J., Bell, L., Peake, A., Poulton, P., Hochman, Z., Thorburn, P., Gaydon, D., Dalgliesh, N., Rodriguez, D., Cox, H., Chapman, S., Doherty, A., Teixeira, E., Sharp, J., Cichota, R., Vogeler, I., Li, F., Wang, E., Hammer, G., Robertson, M., Dimes, J., Carberry, P., Hargreaves, J., MacLeod, N. C. M., Harsdorf, J., Wedgewood, S., and Keating, B. (2013). APSIM — Evolution towards a new generation of agricultural systems simulation, *Environ. Model. Software: Agric. Syst. Model. Software*. Available at: http://www.sciencedirect.com/science/article/pii/S1364815214002102. Accessed on 10 October 2014.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lisazo, J. I., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., and Tsuji, G. Y. (2010). *Decision Support System for Agrotechnology Transfer Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Hsiao, T. C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., and Fereres, E. (2009). AquaCrop-The FAO crop model to simulate yield response to water: III. Parameterization and testing for maize, *Agron. J.*, **101**(3), 448–459.

Hunt, L. A., White, J. W., and Hoogenboom, G. (2001). Agronomic data: advances in documentation and protocols for exchange and use, *Agric. Syst.*, **70**, 477–492.

ICRISAT (International Crops Research Institute for the Semi-Arid Tropics) (1984). *Proc. Int. Symp. Minimum Datasets Agrotechnol. Transfer*, ICRISAT, India, Patancheru, India.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., and Jakas, M. C. (2006). Simulating soil C dynamics with EPIC: Model description and testing against long-term data, *Ecol. Model.*, **192**(3), 362–384.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**(3–4), 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburne, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**, 267–288.

NIST (2012). *Secure Hash Standard (SHS)*, National Institute of Standards and Technology, US Department of Commerce, FIPS Pub #180-4, Gaithersburg, MD, USA. Available at: http://csrc.nist.gov/publications/fips/fips180-4/fips-180-4.pdf. Accessed on 22 September 2014.

Oettli, P., Sultan, B., Baron, C., and Vrac, M. (2011). Are regional climate models relevant for crop yield prediction in West Africa, *Environ. Res. Lett.*, **6**, 014008.

Porter, C. H., Villalobos, C., Holzworth, D., Nelson, R., White, J. W., Athanasiadis, I. N., Janssen, S., Ripoche, D., Cufi, J., Raes, D., Zhang, M., Knapen, R., Sahajpal, R., Boote, K. J., and Jones, J. W. (2014). Harmonization and translation of crop modeling data to ensure interoperability, *Environ. Model. Software*, **62**, 495–508.

Raes, D., Steduto, P., Hsiao, T. C., and Fereres, E. (2009). AquaCrop-The FAO crop model to simulate yield response to water: II. Main algorithms and software description, *Agron. J.*, **101**(3), 438–447.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Antle, J. M., Nelson, G. C., Porter, C. H., and Janssen, S. (2011). *AgMIP Protocols*. Available at: http://research.agmip.org/display/research/AgMIP+Protocols. Accessed on 22 September 2014.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Antle, J. M., Nelson, G. C., Porter, C. H., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G. A., and Winter, J. M. (2013a). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Steduto, P., Hsiao, T. C., Raes, D., and Fereres, E. (2009). AquaCrop-The FAO crop model to simulate yield response to water: I. Concepts and underlying principles, *Agron. J.*, **101**(3), 426–437.

Stöckle, C. O., Donatelli, M., and Nelson, R. (2003). CropSyst, a cropping systems simulation model, *Eur. J. Agron.*, **18**, 289–307.

Sultan B., Roudier, P., Quirion, P., Alhassane, A., Muller, B., Dingkuhn, M. Ciais, P., Guimberteau, M., Traore, S., and Baron, C. (2013). Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa, *Environ. Res. Lett.*, **8**, 014040.

Uehara, G. and Tsuji, G. Y. (1998). "Overview of IBSNAT" in Tsuji, G.Y., Hoogenboom, G., and Thornton, P. K. (eds.), *Understanding Options for Agricultural Production*, Kluwer Academic Publishers, Dordrecht, the Netherlands, pp. 1–7.

Van Diepen, C. A., Wolf, J., van Keulen, H., and Rappoldt, C. (1989). WOFOST: A simulation model of crop production, *Soil Use Manage.*, **5**(1), 16–24.

White, J. W., Hunt, L. A., Boote, K. J., Jones, J. W., Koo, J., Kim, S., Porter, C. H., Wilkens, P. W., and Hoogenboom, G., (2013). Integrated Description of Agricultural Field Experiments and Production: The ICASA Version 2.0 Data Standards, *Computers Electron. Agric.*, **96**, 1–12.

Zhu, Y., Cao, W. X., Shen, W. X., and Tian, Y. C. (2004). Dynamic knowledge model and decision support for rapeseed cultivation management, *Trans. Chin. Soc. Agric. Eng.*, **20**(6), 141–144 (in Chinese with English abstract).

This page intentionally left blank

Section III

Global Estimates of Climate Impacts on Agriculture

This page intentionally left blank

Chapter 7

The AgMIP GRIDded Crop Modeling Initiative (AgGRID) and the Global Gridded Crop Model Intercomparison (GGCMI)

Joshua Elliott[1] and Christoph Müller[2]

[1] *University of Chicago Computation Institute, Chicago, IL, USA*

[2] *Potsdam Institute for Climate Impact Research, Potsdam, Germany*

Introduction

Climate change is a significant risk for agricultural production. Even under optimistic scenarios for climate mitigation action, present-day agricultural areas are likely to face significant increases in temperatures in the coming decades, in addition to changes in precipitation, cloud cover, and the frequency and duration of extreme heat, drought, and flood events (IPCC, 2013). These factors will affect the agricultural system at the global scale by impacting cultivation regimes, prices, trade, and food security (Nelson *et al.*, 2014a).

Global-scale evaluation of crop productivity is a major challenge for climate impact and adaptation assessment. Rigorous global assessments that are able to inform planning and policy will benefit from consistent use of models, input data, and assumptions across regions and time that use mutually agreed protocols designed by the modeling community. To ensure this consistency, large-scale assessments are typically performed on uniform spatial grids, with spatial resolution of typically 10 to 50 km, over specified time-periods. Many distinct crop models and model types have been applied on the global scale to assess productivity and climate impacts, often with very different results (Rosenzweig *et al.*, 2014). These models are based to a large extent on field-scale crop process or ecosystems models and they typically require resolved data on weather, environmental, and farm management conditions that are lacking in many regions (Bondeau *et al.*, 2007; Drewniak *et al.*, 2013; Elliott *et al.*, 2014b; Gueneau *et al.*, 2012; Jones *et al.*, 2003; Liu *et al.*, 2007; Müller and Robertson, 2014; Van den Hoof *et al.*, 2011; Waha *et al.*, 2012; Xiong *et al.*, 2014).

Due to data limitations, the requirements of consistency, and the computational and practical limitations of running models on a large scale, a variety of simplifying assumptions must generally be made regarding prevailing management strategies on the grid scale in both the baseline and future periods. Implementation differences in these and other modeling choices contribute to significant variation among global-scale crop model assessments in addition to differences in crop model implementations that also cause large differences in site-specific crop modeling (Asseng *et al.*, 2013; Bassu *et al.*, 2014).

The AgMIP/ISI-MIP Global Fast-Track Assessment

In 2012 the Agricultural Model Intercomparison and Improvement Project (AgMIP) led a fast-track study, in coordination with the Inter-Sectoral Impacts Model Intercomparison Project (ISI-MIP), to assess climate impacts on global agricultural production. The study involved a preliminary intercomparison of seven global gridded crop models (GGCMs), run for five global climate models and four representative concentration pathways. Results from this global crop modeling assessment were further applied in nine global economic models that computed economic responses to these changes in biophysical productivity, including changes in intensity, land-use patterns, trade, consumption, and food prices. In this section, we summarize several key results from this global fast-track study.

Global climate impacts on key food crops

Across seven GGCMs, five global climate models, and four representative concentration pathways, model agreement on direction of yield changes is found in many major agricultural regions in both low and high latitudes. However, reducing uncertainty in sign of response in mid-latitude regions remains a significant challenge. Crucially, uncertainties related to GGCM simulation of CO_2, nitrogen, and high-temperature effects demonstrated here show that further research is urgently needed to understand better the potential effects of climate change on agricultural production and to devise targeted adaptive strategies. Also, better information is needed on actual cropping systems and growing seasons as well as scenarios for future development of these. Diverging assumptions on agricultural management in GGCM simulations add to the overall uncertainty from climate change and biophysical responses of crops.

Global economic consequences

These global impacts can have serious economic consequences. Agroeconomic models use biophysical model outputs within a general or partial equilibrium economic

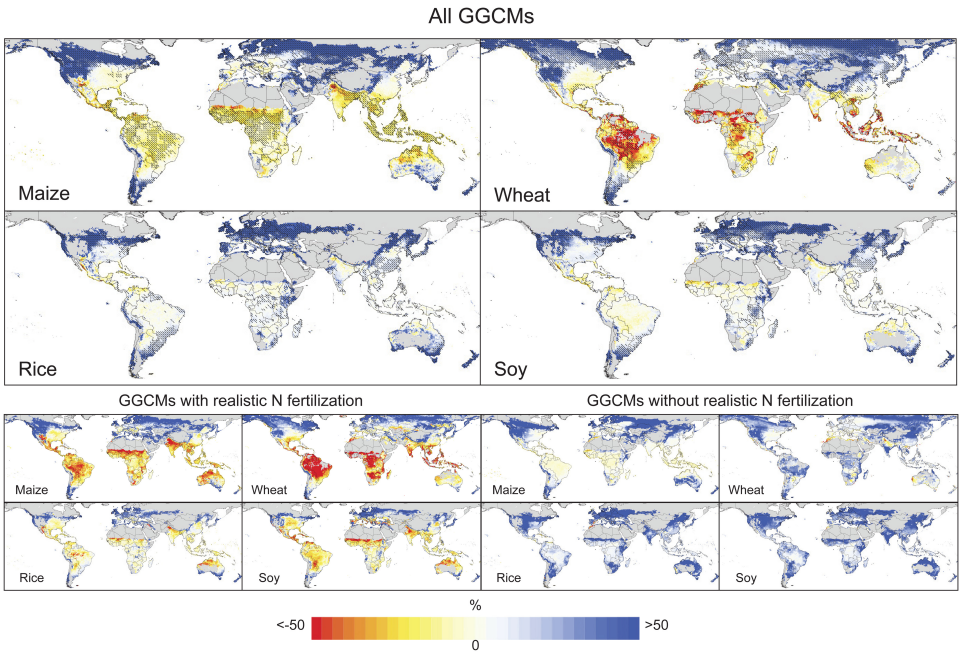


Fig. 1. Median yield changes (%) for RCP8.5 (2070–2099 in comparison to 1980–2010 baseline) with CO_2 effects over all five GCMs × seven GGCMs (six GGCMs for rice) for rainfed (a) maize (35 ensemble members), (b) wheat (35 ensemble members), (c) rice (30 ensemble members), and (d) soy (35 ensemble members). Hatching indicates areas where more than >70% of the ensemble members agree on the directionality of the impact factor. Gray areas indicate historical areas with little to no yield capacity. The bottom eight panels show the corresponding yield change patterns over all five GCMs × four GGCMs with nitrogen stress (20 ensemble members from EPIC (Balkovič *et al.*, 2013), GEPIC (Liu *et al.*, 2007), pDSSAT (Elliott *et al.*, 2014), and PEGASUS (Deryng *et al.*, 2011); except for rice which has 15) (left); and three GGCMs without nitrogen stress (15 ensemble members from GAEZ-IMAGE (Bouwman *et al.*, 2006), LPJ-GUESS (Lindeskog *et al.*, 2013), and LPJmL (Bondeau *et al.*, 2007)). Reproduced from Rosenzweig *et al.* (2014).

modeling framework (Elliott *et al.*, 2014c; Havlík *et al.*, 2013; Hertel *et al.*, 2013; Nelson *et al.*, 2014a, 2014b; Popp *et al.*, 2010; Wise and Calvin, 2011). These models often use relatively simple (though still spatially explicit to varying degrees) representations of food production and climate impacts and combine these with representations of economies, population, markets, and other demand forces at varying degrees of complexity. This allows for parameterization of response options and adaptation mechanisms to prices in a way that is not possible in a purely bio-physical assessment.

As part of the 2012 AgMIP/ISI-MIP fast-track exercise, nine global agro-economic models were driven with biophysical climate impact projections from seven unique scenarios, which were constructed to include outputs from five distinct crop models and two distinct global climate model forcings (Nelson *et al.*,

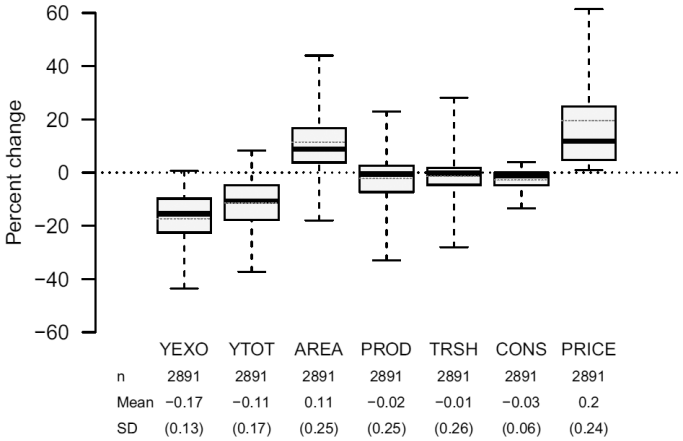


Fig. 2. Variability of key crop and economic model results across crop aggregates ($n = 4$), models ($n = 9$), scenarios ($n = 7$), and regions ($n = 13$). Box-and-whisker plots for key crop and economic model results. The variables YEXO (exogenous crop productivity), YTOT (total crop productivity), AREA (cultivated crop area), PROD (total food production), CONS (total food consumption), and PRICE (aggregate global food price) are reported as percentage change for a climate change scenario relative to the reference scenario (with constant climate) in 2050. TRSH is the change in net imports relative to baseline production in 2050. Boxes represent first and third quartiles and whiskers show 5% to 95% intervals of results. The black thick line represents the median and the thin red dotted line the mean value. Reproduced from Nelson *et al.* (2014a).

2014a). Results from this multi-model assessment are summarized in Fig. 2. While intermodel uncertainty is large, some robust conclusions emerge: Endogenous response (adaptation) ameliorates some fraction of the negative impact, while the remaining effect is compensated in the market by increased production area and increased prices as well as changes in land-use patterns, trade, and, to some lesser extent, food consumption.

Climate, Irrigation, and Adaptation

Conversion from rainfed to irrigated agriculture is likely to be an important mechanism for climate change adaptation in many regions. The extent to which expanded irrigation is possible in the future will be constrained by the availability of freshwater and its use by other sectors. In order to evaluate this, Elliott *et al.* (2014a) used the ISI-MIP fast-track ensemble of six global crop models and 11 global hydrological models. They found that direct climate impacts to maize, soybean, wheat, and rice involve losses of 400–2,600 Pcal (8% to 43% of present-day total calorie production) and that freshwater limitations in some heavily irrigated regions could necessitate reversion of 20–60 Mha of cropland from irrigated to rainfed management, and a further loss of 600–2,900 Pcal (the regions shaded red in Fig. 3). Freshwater abundance in other regions (shaded green in Fig. 3) could help ameliorate these losses by

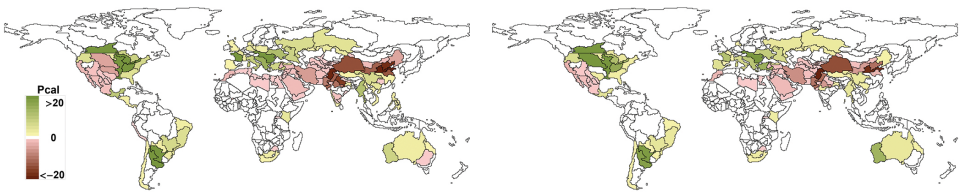


Fig. 3. Potential change in total production of maize, soybean, wheat, and rice at end-of-century given maximal use of available water for increased/decreased irrigation use on what are currently rainfed/irrigated areas in total calories. Left: Median of 156 GCM × GHM × GGCM combinations for scenarios constructed by using GHM (global hydrological module) estimates of present-day irrigation demand. Right: Median of 202 GCM × GHM × GGCM combinations for scenarios constructed by using GGCM estimates of present-day irrigation demand. Reproduced from Elliott *et al.* (2014a).

expanding irrigation agriculture, but substantial investment in infrastructure would be required.

The AgMIP GRIDded Crop Modeling Initiative (AgGRID)

In order to facilitate large-scale multi-model crop productivity and climate impact assessments, and to organize a process to identify and ideally eliminate central deficiencies in model implementation and input data, we launched the AgMIP GRIDded Crop Modeling Initiative (AgGRID, see http://www.agmip.org/ag-grid/) in 2013. AgGRID is a network of researchers working at regional to global scales to address the challenges associated with large-scale assessment by developing and using gridded models and data products. The goal of the initiative is to provide an organizing hub for a new generation of gridded crop modeling and data activities within AgMIP. Interest from the community has been substantial, with more than 21 modeling groups and ten data partners from 11 countries signing up in the first six months.

Biophysical crop growth models can generally be distinguished as either empirical or process-based models, though the distinction is not always straightforward. Most process-based models include some empirical relationships, and many empirical models include partial representations of explicit biophysical relationships. The complexity of models and inputs varies greatly, depending largely on the research questions and applications that motivate development as well as the models' genealogy. At the global scale, we classify the models in AgGRID into three distinct types, each with a broad set of representatives.

Gridded versions of site-based process models

These models are based on field-scale models applied globally by repeated application. Gridded site-based models tend to be the most complex with respect to

processes represented in the model and so generally have high requirements of input data. Field-scale models are often highly calibrated for cultivar and environmental conditions of a single field or set of fields in a region. This is especially important for critical empirical processes, such as radiation-use efficiency (Adam *et al.*, 2011).

Such detailed calibration is generally not performed in gridded global applications due to a lack of available reference data. Instead, cultivar parameters in gridded process models are typically calibrated at a finite set of points, either in the researcher's region of expertise or more broadly, and then key parameters are extrapolated globally with relatively simple algorithms. For management and soil inputs, models are usually driven with compiled and/or extrapolated observational data (e.g., FAO/IIASA/ISRIC/ISSCAS/JRC, 2012; Mueller *et al.*, 2012; Potter *et al.*, 2010; Sacks *et al.*, 2010). Examples of this type of model that participate in the AgGRID GGCMI include pAPSIM (Elliott *et al.*, 2014b), CropSyst (Confalonieri *et al.*, 2006; Stöckle *et al.*, 2003), pDSSAT (Elliott *et al.*, 2014b; Jones *et al.*, 2003;), and four models based on EPIC (i.e., Liu *et al.*, 2007; Xiong *et al.*, 2014).

Dynamic global vegetation and land-surface models

The second major group consists of models that have been implemented into existing land-surface schemes (LSM) or dynamic global vegetation models (DGVMs). LSMs are used in climate models to simulate the energy, water, and sometimes carbon and nitrogen exchanges between the terrestrial biosphere and the atmosphere. Typically, crops have been introduced into land-surface models to improve the representation of seasonal variations in energy and matter (water and carbon) exchanges. DGVMs are developed to study the response of natural ecosystems to climate change and the associated implications for carbon and water cycles. These models have been directly developed for global-scale applications and exchange mechanisms between vegetation and the atmosphere are generally implemented in detail (e.g., stomatal conductance and photosynthesis).

LSM-type models often require weather data inputs at subdaily resolution (which come from the coupled climate model) but, since the focus has typically been on global applications with relatively low spatial resolution, they have few data requirements otherwise. Crop yields are not the primary focus of these models, but have been increasingly important in the applications of many LSMs, such as those participating in GGCMI: CLM-Ag (Gueneau *et al.*, 2012), CLM-Crop (Drewniak *et al.*, 2013), JULES-Crop (Van den Hoof *et al.*, 2011), LPJmL (Bondeau *et al.*, 2007; Müller and Robertson, 2014; Waha *et al.*, 2012), LPJ-GUESS (Lindeskog *et al.*, 2013), and ORCHIDEE (Berg *et al.*, 2011).

Large-area crop models or empirical/process model hybrids

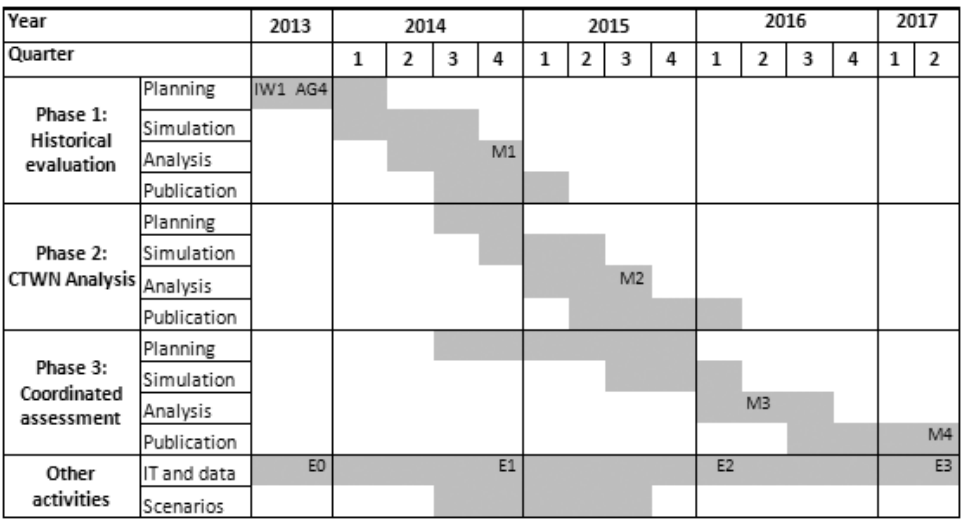
The third group of global gridded crop models consists of those developed explicitly to simulate agricultural production systems at continental or global scales. These models typically include key process-based representations but avoid some of the complexities of the site-based process models (most notably in terms of management and other inputs) in favor of calibrated empirical functions. This provides more flexibility to represent complex systems with hidden variables such as pest outbreaks and enables the computational tractability often necessary to perform large-scale calibration on historical datasets. Examples of these models include CGMS (de Wit and van Diepen, 2008), GLAM (Challinor *et al.*, 2004), MCWLA (Tao *et al.*, 2009a, 2009b), PEGASUS (Deryng *et al.*, 2011), and PRYSBI-2 (Okada *et al.*, 2011).

In addition to model partners, AgGRID also works with data providers from around the world to generate the best-available datasets for weather/climate forcing, fertilizer, and other applied inputs, planting dates and growing-season lengths, gridded soil profiles, and time-series crop-specific observational yield records for output validation (Table 3). A substantial data requirement for AgGRID is the need for daily time-series of detailed weather data over many years (AgGRID also provides subdaily versions of several weather datasets, which are required by some models). Primary variables in the weather series are daily maximum and minimum temperatures, precipitation, and incoming solar radiation. Many gridded crop models also take one or more secondary weather variables if available, such as surface wind speeds and vapor pressure. Key environmental data for the gridded crop models are typically encoded in soil and surface profiles and include slope and aspect, albedo, surface permeability, and soil water-retention properties, organic carbon, nitrogen, pH, rooting depth, etc. Key management inputs include nitrogen fertilizer and manure application rates, irrigation capacity, and cultivar choice. Secondary management inputs can include phosphorus and potassium fertilizer application rates, pest control, and tillage methods.

The Global Gridded Crop Model Intercomparison (GGCMI)

Following completion of the fast-track project, designed to provide rapid global analysis for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5), the project has rapidly expanded. The resulting Global Gridded Crop Model Intercomparison (GGCMI; see http://www.agmip.org/ag-grid/ggcmi), the flagship project of the AgGRID initiative, is proceeding in three overlapping phases (Table 1) and includes more than 20 modeling groups (Table 2) and eight data partners (Table 3) conducting hundreds of coordinated historical and future simulations for model intercomparison and improvement and climate impact assessment.

Table 1. Three year time-line for the AgMIP GGCMI. Key meetings and data delivery targets are indicated. For the report of the Fourth Annual Global Workshop see Appendix 3 in Part 1 of this volume.



IW1 = First Impacts World meeting in Potsdam, Germany May 27–30; AG4 = fourth Annual AgMIP global workshop; M[1–4] = planned project meetings; E[0–3] = public launches of the Phase 0–Phase 3 archives. CTWN = carbon, temperature, water, nitrogen.

Phase 1: Historical simulation and model evaluation (2014)

In Phase 1, GGCMI participants conduct model simulations globally by using harmonized inputs and nine distinct reanalysis-based historical weather products spanning 1948–present. The focus of this phase is model intercomparison and identification of general and model-specific skills and deficiencies, validation, and improvement, as well as evaluation of extreme events in the historical record.

Phase 2: Analysis of carbon, temperature, water, and nitrogen (CTWN) sensitivity (2015)

In Phase 2, GGCMI participants conduct a multi-dimensional sensitivity study of model response to CO_2, temperature, water, and nitrogen organized around a set of simulations that are driven by perturbed versions of the historical and harmonization data products prepared in Phase 1. Results will be used both to analyze model sensitivity and to facilitate better understanding of model behavior, as well as to develop high-resolution multi-dimensional response surfaces (Ruane *et al.*, 2014) that can be aggregated to arbitrary administrative or environmental boundaries and used as efficient multi-model emulators.

Table 2. Models and groups engaged thus far in the AgMIP GGCMI team.

Model	Lead institution	Contact(s)	Model type and notes
pDSSAT †|E	University of Chicago, USA	jelliott@ci.uchicago.edu	Site-based process (Elliott *et al.*, 2014b) (DSSAT 4.5, Jones *et al.*, 2003)
EPIC-Boku*|E	Boku, Austria	erwin.schmid@boku.ac.at	Site-based process (EPIC v0810) (Balkovič *et al.*, 2013)
GEPIC*|E	EAWAG, Switzerland	folberth@iiasa.ac.at	Site-based process (EPIC v0810) (Liu *et al.*, 2007)
pAPSIM †E	University of Chicago, USA	jelliott@ci.uchicago.edu	Site-based process (APSIM v7.5) (Elliott *et al.*, 2014b; Keating *et al.*, 2003)
EPIC-IIASA*E	IIASA, Austria	khabarov@iiasa.ac.at	Site-based process (EPIC v0810) (Balkovič *et al.*, 2013)
EPIC-TAMU*E	TAMU and UMD, USA	cizaurra@umd.edu	Site-based process (EPIC v1102) (Izaurralde *et al.*, 2006)
CropSystO	WSU, USA	stockle@wsu.edu	Site-based process (Stöckle *et al.*, 2003)
DAYCENTO	Colorado State, USA	dennis.ojima@colostate.edu	Site-based process (Stehfest *et al.*, 2007)
LPJmL|	PIK, Germany	cmueller@pik-potsdam.de	DGVM (Bondeau *et al.*, 2007; Müller and Robertson, 2014)
ORCHIDEE	IPSL, France	nathalie.de-noblet@lsce.ipsl.fr	DGVM (de Noblet-Ducoudre *et al.*, 2004)
LPJ-GUESS|	KIT, Germany	almut.arneth@kit.edu	DGVM (Lindeskog *et al.*, 2013; Smith *et al.*, 2001)
JULES-cropO	Met Office, UK	pete.falloon@metoffice.gov.uk	DGVM (Van den Hoof *et al.*, 2011)
CLM-Crop	LBNL, USA	adjones@lbl.gov	DGVM (Levis *et al.*, 2012; Drewniak *et al.*, 2013)
PEGASUS|	Tyndall, UEA, UK	d.deryng@uea.ac.uk	Empirical/process (Deryng *et al.*, 2011; Deryng *et al.*, 2014)
GLAMO	SEE, Leeds, UK	a.j.challinor@leeds.ac.uk	Empirical/process (Challinor *et al.*, 2004)
CGMS	WUR, NL	allard.dewit@wur.nl	Empirical/process (WOFOST) (van Diepen *et al.*, 1989; Supit *et al.*, 1994)

(*Continued*)

Table 2. (*Continued*)

Model	Lead institution	Contact(s)	Model type and notes
PRYSBI-2	NIAES, Japan	iizumit@affrc.go.jp	Empirical/process (Okada *et al.*, 2011)
MCWLA[O]	IGSNRR, China	taofl@igsnrr.ac.cn	Empirical/process (Tao and Zhang, 2012)

[†]pDSSAT and pAPSIM are both part of the pSIMS framework; they use inputs and assumptions that are as closely harmonized as is possible, to allow a more direct comparison of intermodel differences.
*Four contributing GGCMs are built from the field-scale EPIC model and will be used for detailed explorations of the effects of different assumptions and configurations even within the same model.
[|]Model participating in the 2012/2013 AgMIP/ISI-MIP fast-track.
[E]EPIC, DSSAT, and APSIM-based models will perform additional scenarios using alternative methods to model evapotranspiration in order to understand better the effect this important model choice has on assessments.
[O]Models expected to participate starting in Phase 2.

Table 3. Some key data products and partners engaged in AgMIP GGCMI.

Key product(s)	Institution(s)	Contact(s)	Notes
WATCH/WFDEI, Weedon-2011	Met Office UK *et al.*	heinke@pik-potsdam.de	Hist. climate (ERA)
AgMERRA	NASA GISS, USA	alexander.c.ruane@nasa.gov	Hist. climate (MERRA and CFSR)
AgCFSR	NASA GISS, USA	alexander.c.ruane@nasa.gov	Hist. climate (MERRA and CFSR)
Princeton Global Forcing	Princeton University, USA	justin@princeton.edu	Hist. climate (NCAR1)
GRASP (Iizumi, 2014) Iizumi, 2013	NIAES, Japan	iizumit@affrc.go.jp	Hist. climate (JRA) Crop yields, 1982–2006
Sacks, 2010	University of Wisconsin SAGE	D.Deryng@uea.ac.uk	Crop-specific sowing calendars
Mueller, 2012 & Foley, 2010	University of Minnesota, USA	muell512@umn.edu	Crop-specific NPK fertilizer
Potter, 2010 & Monfreda, 2008	McGill University, Canada	navin.ramankutty@mcgill.ca	Fertilizer and yield data

Note: Products identified by [Author, Year] refer to publications of the form [Author *et al.*, Year] in the bibliography.

Phase 3: Coordinated assessment (2016)

In Phase 3, GGCMI participants will conduct an AgMIP-led comprehensive assessment of climate vulnerabilities, impacts, and adaptations by using a new set of

future climate forcings from CMIP5 and CORDEX and a detailed set of adaptation scenarios developed in the AgMIP representative agricultural pathways (RAPs) framework (Part 1, Chapter 5 in this volume). This assessment will provide support for decision-makers in processes such as the UNFCCC (United Nations Framework Convention on Climate Change) meetings and the IPCC (Intergovernmental Panel on Climate Change).

Conclusions

The AgMIP/ISI-MIP fast-track simulations have demonstrated that there is great interest in global-scale climate change impact assessments, that economic assessments can be usefully informed by global-scale crop modeling, and that there is an emerging modeling community that is able to perform large-scale gridded crop model simulations with a broad set of models. This first intercomparison has, however, also demonstrated that there is great need to understand better the reasons for the great differences in projected climate change impacts.

The design of the GGCMI protocols is dedicated to establishing a better understanding of why models differ, and to dissect the contribution from inputs on weather drivers as well as management systems and fertilizer use. In concert with enhanced understanding in site-based crop models in the AgMIP crop-specific activities, such as AgMIP wheat (Asseng *et al.*, 2013) and AgMIP maize (Bassu *et al.*, 2014), models will be improved to facilitate better future assessments of climate change impacts on crop growth.

Future impact assessments will also require an improved understanding of how agricultural production systems will change over the 21st century. Here, the GGCMI will greatly benefit from the established interaction with the global agroeconomic modeling community in AgMIP, which projects changes in farm-management conditions (such as land-use patterns and intensities) and with the AgMIP teams that are developing global-scale representative agricultural pathways (RAPs; see Part 1, Chapter 5 in this volume), in concert with the shared socio-economic pathways (SSPs; Kriegler *et al.*, 2012).

References

Adam, M., Van Bussel, L. G. J., Leffelaar, P. A., Van Keulen, H., and Ewert, F. (2011). Effects of modelling detail on simulated potential crop yields under a wide range of climatic conditions, *Ecol. Model.*, **222**, 131–143.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rotter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R.,

Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stockle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Balkovič, J., van der Velde, M., Schmid, E., Skalský, R., Khabarov, N., Obersteiner, M., Stürmer, B., and Xiong, W. (2013). Pan-European crop modelling with EPIC: Implementation, up-scaling and regional crop yield validation, *Agric. Syst.*, **120**, 61–75.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A. R., Kersebaum, K. C., Kumar, N. S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M. V., Soo, H. K., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., and Waha, K. (2014). Do various maize crop models give the same responses to climate change factors?, *Global Change Biol.*, **20**, 2301–2320.

Berg, A., Sultan, B., and de Noblet-Ducoudre, N. (2011). Including tropical croplands in a terrestrial biosphere model: Application to West Africa, *Clim. Change*, **104**, 755–782.

Bondeau, A., Smith, P. C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-Campen, H., Müller, C., Reichstein, M., and Smith, B. (2007). Modelling the role of agriculture for the 20th century global terrestrial carbon balance, *Global Change Biol.*, **13**, 679–706.

Bouwman A. F., Kram, T., Klein, T., and Goldewijk. K. (eds.) (2006). *Integrated Modelling of Global Environmental Change. An Overview of IMAGE 2.4*, PBL Netherlands Environmental Assessment Agency, The Hague.

Challinor, A. J., Wheeler, T. R., Craufurd, P. Q., Slingo, J. M., and Grimes, D. I. F. (2004). Design and optimisation of a large-area process-based model for annual crops, *Agric. Forest Meteorol.*, **124**, 99–120.

Confalonieri, R., Gusberti, D., Bocchi, S., and Acutis, M. (2006). The CropSyst model to simulate the N balance of rice for alternative management, *Agron. Sustain. Dev.*, **26**, 241–249.

de Noblet-Ducoudre, N., Gervois, S., Ciais, P., Viovy, N., Brisson, N., Seguin, B., and Perrier, A. (2004). Coupling the Soil-Vegetation-Atmosphere-Transfer Scheme ORCHIDEE to the agronomy model STICS to study the influence of croplands on the European carbon and water budgets, *Agronomie*, **24**, 397–407.

de Wit, A. J. W. and van Diepen, C. A. (2008). Crop growth modelling and crop yield forecasting using satellite-derived meteorological inputs, *Int. J. Appl. Earth Obs. Geoinf.*, **10**, 414–425.

Deryng, D., Sacks, W. J., Barford, C. C., and Ramankutty, N. (2011). Simulating the effects of climate and agricultural management practices on global crop yield, *Global Biogeochem. Cycles*, **25**, GB2006.

Deryng, D., Conway, D., Ramankutty, N., Price, J., and Warren, R. (2014). Global crop yield response to extreme heat stress under multiple climate change futures, *Environ. Res. Lett.*, **9**, 034011.

Drewniak, B., Song, J., Prell, J., Kotamarthi, V. R., and Jacob, R. (2013). Modeling agriculture in the Community Land Model, *Geosci. Model Dev.*, **6**, 495–515.

Elliott, J., Deryng, D., Müller, C., Frieler, K., Konzmann, M., Gerten, D., Glotter, M., Flörke, M., Wada, Y., Best, N., Eisner, S., Fekete, B. M., Folberth, C., Foster, I., Gosling, S. N., Haddeland, I., Khabarov, N., Ludwig, F., Masaki, Y., Olin, S., Rosenzweig, C., Ruane, A. C., Satoh, Y., Schmid, E., Stacke, T., Tang, Q., and Wisser, D. (2014a). Constraints and potentials of future irrigation water availability on agricultural production under climate change, *Proc. Natl. Acad. Sci.*, **111**, 3239–3244.

Elliott, J., Kelly, D., Chryssanthacopoulos, J., Glotter, M., Jhunjhnuwala, K., Best, N., Wilde, M., and Foster, I. (2014b). The parallel system for integrating impact models and sectors, *Environ. Model. Software*, **62**, 509–516.

Elliott, J., Sharma, B., Best, N., Glotter, M., Dunn, J. B., Foster, I., Miguez, F., Mueller, S., and Wang, M. Q. (2014c). A spatial modeling framework to evaluate domestic biofuel-induced potential land use changes and emissions, *Environ. Sci. Technol*, **48**(4), 2488–2496.

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., Balzer, C., Bennett, E. M., Carpenter, S. R., Hill, J., Monfreda, C., Polasky, S., Rockstrom, J., Sheehan, J., Siebert, S., Tilman, D., and Zaks, D. P. M. (2011). Solutions for a cultivated planet, *Nature*, **478**, 337–342.

Gueneau, A., Schlosser, C. A., Strzepek, K. M., Gao, X., and Monier, E. (2012). *CLM-AG: An Agriculture Module for the Community Land Model version 3.5*, MIT Joint Program on the Science and Policy of Global Change, report 229. Available at: http://hdl.handle.net/1721.1/73007. Accessed on 20 September 2014.

Havlík, P., Valin, H., Mosnier, A., Obersteiner, M., Baker, J. S., Herrero, M., Rufino, M. C., and Schmid, E. (2013). Crop Productivity and the Global Livestock Sector: Implications for Land Use Change and Greenhouse Gas Emissions, *Am. J. Agric Econ*, **95**, 442–448.

Hertel, T., Steinbuks, J., and Baldos, U. (2013). Competition for land in the global bioeconomy, *Agric. Econ.*, **44**, 129–138.

Iizumi, T., Okada, M., and Yokozawa M. (2014). A meteorological forcing data set for global crop modeling: Development, evaluation, and intercomparison, *J. Geophys. Res. Atmos.*, **119**, 363–384.

Iizumi, T., Yokozawa, M., Sakurai, G., Travasso, M. I., Romanernkov, V., Oettli, P., Newby, T., Ishigooka, Y., and Furuya, J. (2013). Historical changes in global yields: major cereal and legume crops from 1982 to 2006, *Global Ecology and Biogeography*, **23**(3), 346–357.

IPCC (2013). "Summary for Policymakers", in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., V., B., and Midgley, P. M. (eds.), Cambridge University Press, Cambridge.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., and Jakas, M. C. Q. (2006). Simulating soil C dynamics with EPIC: Model description and testing against long-term data, *Ecol. Model.*, **192**, 362–384.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**, 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**, 267–288.

Kriegler, E., O'Neill, B. C., Hallegatte, S., Kram, T., Lempert, R. J., Moss, R. H., and Wilbanks, T. (2012). The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways, *Global Environ. Change*, **22**, 807–822.

Levis, S., Bonan, G. B., Kluzek, E., Thornton, P. E., Jones, A., Sacks, W. J., and Kucharik, C. J. (2012). Interactive Crop Management in the Community Earth System Model (CESM1): Seasonal Influences on Land-Atmosphere Fluxes, *J. Clim.*, **25**, 4839–4859.

Lindeskog, M., Arneth, A., Bondeau, A., Waha, K., Seaquist, J., Olin, S., and Smith, B. (2013). Implications of accounting for land use in simulations of ecosystem carbon cycling in Africa, *Earth Syst. Dynam.*, **4**, 385–407.

Liu, J. G., Williams, J. R., Zehnder, A. J. B., and Yang, H. (2007). GEPIC — modelling wheat yield and crop water productivity with high resolution on a global scale, *Agric. Syst.*, **94**, 478–493.

Monfreda, C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, *Global Biogeochem. Cycles*, **22**(1).

Mueller, N. D., Gerber, J. S., Johnston, M., Ray, D. K., Ramankutty, N., and Foley, J. A. (2012). Closing yield gaps through nutrient and water management, *Nature*, **490**, 254–257.

Müller, C. and Robertson, R. (2014). Projecting future crop productivity for global economic modeling, *Agric. Econ.*, **45**, 37–50.

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., Robinson, S., Schmid, E., Schmitz, C., Tabeau, A., and Willenbockel, D. (2014a). Climate change effects on agriculture: Economic responses to biophysical shocks, *Proc. Natl. Acad. Sci.*, **111**, 3274–3279.

Nelson, G. C., van der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., von Lampe, M., Mason d'Croz, D., van Meijl, H., Müller, C., Reilly, J., Robertson, R., Sands, R. D., Schmitz, C., Tabeau, A., Takahashi, K., Valin, H., and Willenbockel, D. (2014b). Agriculture and climate change in global scenarios: why don't the models agree, *Agric. Econ.*, **45**, 85–101.

Okada, M., Iizumi, T., Hayashi, Y., and Yokozawa, M. (2011). Modeling the multiple effects of temperature and radiation on rice quality, *Environ. Res. Lett.*, **6**, 034031.

Popp, A., Lotze-Campen, H., and Bodirsky, B. (2010). Food consumption, diet shifts and associated non-CO2 greenhouse gases from agricultural production, *Global Environ. Change*, **20**, 451–462.

Potter, P., Ramankutty, N., Bennett, E. M., and Donner, S. D. (2010). Characterizing the Spatial Patterns of Global Fertilizer Application and Manure Production, *Earth Interact.*, **14**, 1–22.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., and Jones, J. W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison, *Proc. Natl. Acad. Sci.*, **111**, 3268–3273.

Ruane, A. C., McDermid, S., Rosenzweig, C., Baigorria, G. A., Jones, J. W., Romero, C. C., and DeWayne Cecil, L. (2014). Carbon–Temperature–Water change analysis for peanut production under climate change: A prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP), *Global Change Biol.*, **20**, 394–407.

Sacks, W. J., Deryng, D., Foley, J. A., and Ramankutty, N. (2010). Crop planting dates: An analysis of global patterns, *Global Ecol. Biogeog.*, **19**, 607–620.

Smith, B., Prentice, I. C., and Sykes, M. T. (2001). Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space, *Global Ecol. Biogeog.*, **10**, 621–637.

Stehfest, E., Heistermann, M., Priess, J. A., Ojima, D. S., and Alcamo, J. (2007). Simulation of global crop production with the ecosystem model DayCent, *Ecol. Model.*, **209**, 203–219.

Stöckle, C. O., Donatelli, M., and Nelson, R. (2003). CropSyst, a cropping systems simulation model, *Eur. J. Agron.*, **18**, 289–307.

Supit, I., Hooijer, A. A., and van Diepen, C. A., 1994. *System description of the WOFOST 6.0 crop simulation model implemented in CGMS*, EUR;15956 EN, Office for Official Publications of the European Commission, Luxembourg.

Tao, F., Yokozawa, M., and Zhang, Z. (2009a). Modelling the impacts of weather and climate variability on crop productivity over a large area: A new process-based model development, optimization, and uncertainties analysis, *Agric. Forest Meteorol.*, **149**, 831–850.

Tao, F. and Zhang, Z. (2012). Climate Change, High-Temperature Stress, Rice Productivity, and Water Use in Eastern China: A New Superensemble-Based Probabilistic Projection, *J. Appl. Meteorol. Clim.*, **52**, 531–551.

Tao, F., Zhang, Z., Liu, J., and Yokozawa, M. (2009b). Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection, *Agric. Forest Meteorol.*, **149**, 1266–1278.

Van den Hoof, C., Hanert, E., and Vidale, P. L. (2011). Simulating dynamic crop growth with an adapted land surface model — JULES-SUCROS: Model development and validation, *Agric. Forest Meteorol.*, **151**, 137–153.

van Diepen, C. A., Wolf, J., van Keulen, H., and Rappoldt, C. (1989). WOFOST: A simulation model of crop production, *Soil Use Manage.*, **5**, 16–24.

Waha, K., van Bussel, L. G. J., Müller, C., and Bondeau, A. (2012). Climate-driven simulation of global crop sowing dates, *Global Ecol. Biogeog.*, **21**, 247–259.

Wise, M. and Calvin, K. (2011). *GCAM 3.0 Agriculture and Land Use: Technical Description of Modeling Approach*, Pacific Northwest National Laboratory, Richland, WA, USA.

Xiong, W., Balkovič, J., van der Velde, M., Zhang, X., Izaurralde, R. C., Skalský, R., Lin, E., Mueller, N., and Obersteiner, M. (2014). A calibration procedure to improve global rice yield simulations with EPIC, *Ecol. Model.*, **273**, 128–139.

This page intentionally left blank

Chapter 8

The AgMIP Coordinated Climate-Crop Modeling Project (C3MP): Methods and Protocols

Sonali P. McDermid[1,2], Alexander C. Ruane[2], Cynthia Rosenzweig[2], Nicholas I. Hudson[3], Monica D. Morales[3], Prabodha Agalawatte[55], Shakeel Ahmad[60], L. R. Ahuja[4], Istiqlal Amien[54], Saseendran S. Anapalli[4], Jakarat Anothai[5], Senthold Asseng[6], Jody Biggs[63], Federico Bert[8], Patrick Bertuzzi[9], Virender S. Bhatia[10], Marco Bindi[11], Ian Broad[12], Davide Cammarano[13], Ramiro Carretero[8], Ashfaq Ahmad Chattha[50], Uran Chung[14], Stephanie Debats[56], Paola Deligios[64], Giacomo De Sanctis[15], Thanda Dhliwayo[14], Benjamin Dumont[7], Lyndon Estes[56], Frank Ewert[16], Roberto Ferrise[11], Thomas Gaiser[16], Guillermo Garcia[8], Sika Gbegbelegbe[17], Vellingiri Geethalakshmi[18], Edward Gerardeaux[19], Richard Goldberg[3], Brian Grant[20], Edgardo Guevara[21], Jonathan Hickman[22], Holger Hoffmann[18], Huanping Huang[23], Jamshad Hussain[50], Flavio Barbosa Justino[24], Asha S. Karunaratne[25], Ann-Kristin Koehler[26], Patrice K. Kouakou[61], Soora Naresh Kumar[27], Arunachalam Lakshmanan[18], Mark Lieffering[57], Xiaomao Lin[28], Qunying Luo[29], Graciela Magrin[21], Marco Mancini[11], Fabio Ricardo Marin[52], Anna Dalla Marta[11], Yuji Masutomi[30], Theodoros Mavromatis[31], Greg McLean[32], Santiago Meira[21], Monoranjan Mohanty[33], Marco Moriondo[11], Wajid Nasim[60], Lamyaa Negm[34], Francesca Orlando[11], Simone Orlandini[11], Isik Ozturk[35], Helena Maria Soares Pinto[52], Guillermo Podesta[53], Zhiming Qi[36], Johanna Ramarohetra[37], Muhammad Habib ur Rahman[50], Helene Raynal[38], Gabriel Rodriguez[21], Reimund Rötter[58], Vaishali Sharda[6], Lu Shuo[39], Ward Smith[20], Val Snow[59], Afshin Soltani[40], K. Srinivas[41], Benjamin Sultan[66], Dillip Kumar Swain[42], Fulu Tao[43], Kindie Tesfaye[44], Maria I. Travasso[21], Giacomo Trombi[11], Alex Topaj[65], Eline Vanuytrecht[51], Federico E. Viscarra[45], Syed Aftab Wajid[50], Enli Wang[46], Hong Wang[47], Jing Wang[39], Erandika Wijekoon[55], Lee Byun-Woo[48], Yang Xiaoguang[39], Ban Ho Young[48], Jin I. Yun[49], Zhigan Zhao[39], and Lareef Zubair[55]

[1]*New York University, New York, NY, USA*

[2]*NASA Goddard Institute for Space Studies, New York, NY, USA*

[3]*Columbia University Center for Climate Systems Research, New York, New York*

[4]*United States Department of Agriculture, Agricultural Research Service, Ames, IA, USA*
[5]*Prince of Songkla University, Hat Yai, Thailand*
[6]*University of Florida, Gainesville, FL, USA*
[7]*Université de Liège, Liège, Belgium*
[8]*Universidad de Buenos Aires, Buenos Aires, Argentina*
[9]*INRA, Avignon, France*
[10]*National Research Centre for Soybean, Indore, India*
[11]*University of Florence, Florence, Italy*
[12]*University of Queensland, QLD, Australia*
[13]*James Hutton Institute, Dundee, UK*
[14]*International Maize and Wheat Improvement Center (CIMMYT), Texcoco, Mexico*
[15]*European Commission, Joint Research Center, Ispra, Italy*
[16]*University of Bonn, Bonn, Germany*
[17]*International Maize and Wheat Improvement Center (CIMMYT), Nairobi, Kenya*
[18]*Tamil Nadu Agricultural University, Coimbatore, India*
[19]*CIRAD, Paris, France*
[20]*Agriculture and Agri-Food, Ontario, Canada*
[21]*National Agricultural Technology Institute (INTA), Pergamino, Argentina*
[22]*Agriculture and Food Security Center, Columbia University, New York, NY, USA*
[23]*Chinese Academy of Agricultural Sciences, Beijing, China*
[24]*Universidade Federal de Viçosa, Viçosa, Brazil*
[25]*Sabaragamuwa University of Sri Lanka, Belihuloya, Sri Lanka*
[26]*Univesity of Leeds, Leeds, UK*
[27]*IARI, New Delhi, India*
[28]*Kansas State University, Manhattan, Kansas, USA*
[29]*University of Technology, Sydney, Australia*
[30]*College of Agriculture, Ibaraki University, Japan*
[31]*Aristotle University of Thessaloniki, Thessaloniki, Greece*
[32]*Queensland Dept of Agriculture, Fisheries and Forestry, QLD, Australia*
[33]*Indian Institute of Soil Science, Bhopal, India*
[34]*NC State University, Raleigh, NC, USA*

[35]*Aarhus University, Tjele, Denmark*

[36]*McGill University, Sainte-Anne-de-Bellevue, QC, Canada*

[37]*L'Institut de recherche pour le développement (IRD), Paris, France*

[38]*National Institute of Agronomic Research (INRA), Toulouse, France*

[39]*College of Agronomy and Biotechnology, China Agricultural University, Beijing, China*

[40]*Gorgan University of Agricultural Sciences & Natural Resources, Gorgan, Iran*

[41]*International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad, India*

[42]*Indian Institute of Technology Kharagpur, Kharagpur, India*

[43]*Chinese Academy of Sciences, Institute of Geographical Sciences and Natural Resources Research, Beijing, China*

[44]*International Maize and Wheat Improvement Center (CIMMYT), Addis Ababa, Ethiopia*

[45]*Fundacion Amigos de la Naturaleza (FAN), Santa Cruz, Bolivia*

[46]*Commonwealth Scientific and Industrial Research Organisation Land and Water, Canberra, Australia*

[47]*SPARC/AAFC, Swift Current, Canada*

[48]*Seoul National University, Seoul, Republic of Korea*

[49]*Kyung Hee University, Yongin, Republic of Korea*

[50]*University of Agriculture, Faisalabad, Pakistan*

[51]*KU Leuven, Leuven, Belgium*

[52]*University of São Paulo, ESALQ, Piracicaba, SP, Brazil*

[53]*University of Miami, Miami, Florida, USA*

[54]*Agro-climatology and Hydrology Research Institute, Bogor, Indonesia*

[55]*Foundation for Environment Climate and Technology, Kandy, Sri Lanka*

[56]*Princeton University, Princeton, NJ, USA*

[57]*AgResearch New Zealand, Palmerston North, New Zealand*

[58]*MTT Agrifood Research Finland, Mikkeli, Finland*

[59]*AgResearch Limited, Christchurch, New Zealand*

[60]*COMSATS-Institute of Information Technology (CIIT), Vehari, Pakistan*

[61]*Centre d'Etude Régional pour l'Amélioration de l'Adaptation à la Sécheresse (CERAAS), Thiès, Sénégal*

[62]*Bahauddin Zakariya University, Multan, Pakistan*

[63]*CSIRO Ecosystem Sciences, Brisbane, Australia*

[64]*University of Sassari, Sassari, Italy*

[65]*Agrophysical Research Institute, Saint-Petersburg, Russia*

[66]*Sorbonne Universités, Paris, France*

This page intentionally left blank

Introduction

Background and motivation

Climate change is expected to alter a multitude of factors important to agricultural systems, including pests, diseases, weeds, extreme climate events, water resources, soil degradation, and socio-economic pressures. Changes to carbon dioxide concentration ($[CO_2]$), temperature, and water (CTW) will be the primary drivers of change in crop growth and agricultural systems. Therefore, establishing the CTW-change sensitivity of crop yields is an urgent research need and warrants diverse methods of investigation.

Crop models provide a biophysical, process-based tool to investigate crop responses across varying environmental conditions and farm management techniques, and have been applied in climate impact assessment by using a variety of methods (White *et al.*, 2011, and references therein). However, there is a significant amount of divergence between various crop models' responses to CTW changes (Rötter *et al.*, 2011). While the application of a site-based crop model is relatively simple, the coordination of such agricultural impact assessments on larger scales requires consistent and timely contributions from a large number of crop modelers, each time a new global climate model (GCM) scenario or downscaling technique is created. A coordinated, global effort to rapidly examine CTW sensitivity across multiple crops, crop models, and sites is needed to aid model development and enhance the assessment of climate impacts (Deser *et al.*, 2012).

To fulfill this need, the Coordinated Climate-Crop Modeling Project (C3MP) (Ruane *et al.*, 2014) was initiated within the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013). The submitted results from C3MP Phase 1 (February 15, 2013–December 31, 2013) are currently being analyzed. This chapter serves to present and update the C3MP protocols, discuss the initial participation and general findings, comment on needed adjustments, and describe continued and future development.

AgMIP aims to improve substantially the climate, crop, and economic simulation tools that are used to characterize the agricultural sector, to assess future world food security under changing climate conditions, and to enhance adaptation capacity both globally and regionally. To understand better and improve the modeled crop responses, AgMIP has conducted detailed crop model intercomparisons at closely observed field sites for wheat (Asseng *et al.*, 2013), rice (Li *et al.*, in review), maize (Bassu *et al.*, 2014), and sugarcane (Singels *et al.*, 2013). A coordinated modeling exercise was one of the original motivations for AgMIP, and C3MP provides rapid estimation of crop responses to CO_2, water, and temperature (CTW) changes,

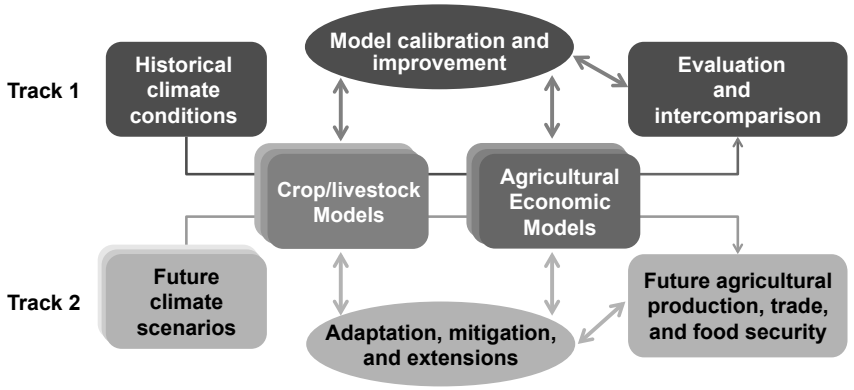


Fig. 1. The AgMIP two-track approach. Track 1: Multi-model intercomparison and improvement, Track 2: Climate change multi-model assessment. C3MP is a pilot activity for climate and crop activities of Track 2. Reproduced from Rosenzweig *et al.* (2012), with permission from Elsevier.

adding dimension and insight into the crop model intercomparisons, while facilitating interactions within the global community of modelers. C3MP also contributes a fast-track, multi-model climate sensitivity assessment for the AgMIP climate and crop modeling teams on Research Track 2 (Fig. 1), which seeks to understand the impact of projected climatic changes on crop production and food security (Rosenzweig *et al.*, 2013; Ruane *et al.*, 2014).

Objectives and ongoing contributions to greater AgMIP activities

C3MP is engaging the global community of crop modelers to expand the understanding of crop responses and sensitivities to the projected range of CTW changes; mobilizing and engaging the international community of crop modelers in coordinated climate-crop assessments; and improving the overall utility of crop model applications (Rötter *et al.*, 2011; White *et al.*, 2011).

To achieve these goals, C3MP participants are contributing to four major objectives:

- To expand further the international network of crop modelers and continue to build the C3MP database of simulation sites through a strong web-based community and information-exchange platform.
- To explore the range of simulated agricultural responses to CTW changes through rapid, easily executed sensitivity tests and associated impact-response emulators.
- To identify climate-related vulnerabilities highlighted by these analyses across regions, among crops, and between different farming systems.
- To analyze uncertainty that arises from projected climate changes and the impacts on crop production across crops, models, and sites.

In addition, participants are experiencing a wide range of benefits by contributing to C3MP, including:

- Representation of their individual research sites and results in global studies.
- Recognition of contributions to the C3MP database.
- International networking and collaborative research opportunities.
- Early access to the full database of global C3MP results.
- Potential co-authorship of C3MP studies.

Furthermore, interactions among participants using different crop models across a multitude of sites are fostering model improvement and development.

C3MP is also contributing site-based results from many agricultural regions to other ongoing AgMIP crop modeling activities, including the detailed crop model intercomparisons at platinum sentinel sites led by the AgMIP crops team (Asseng *et al.*, 2013; Bassu *et al.*, 2014; Li *et al.*, 2014; Singels *et al.*, 2013). These sentinel sites represent the highest quality observed experiment data for model intercomparisons, evaluation, and improvement, with the full complement of variables, including in-season and end-of-season measurements (more information is available at http://www.agmip.org/sentinel-sites/). Additionally, C3MP is aiding the utilization and improvement of global gridded crop models by the AgMIP GRIDded Crop Modeling Initiative (AgGRID) that simulates global agricultural production on high-resolution grids (e.g., Rosenzweig *et al.*, 2013; see also Part 1, Chapter 7 in this volume).

The C3MP Methodology and Participation Protocols

C3MP methodology

The C3MP methods and protocols are described in detail in Ruane *et al.* (2014), and are summarized here. Each C3MP contributor simulates yields with their site-calibrated crop model under a common set of 99 sensitivity tests designed to sample the specified CTW change uncertainty space uniformly. These CTW changes lie within a specified range (shown in Table 1) that spans the climate extremes projected by GCMs for the Fifth Coupled Model Intercomparison Project (CMIP5; Taylor *et al.*, 2009) for the majority of agricultural lands (Ruane *et al.*, 2014).

Table 1. Ranges tested in C3MP climate sensitivity simulations.

Climate metric	Lower bound	Upper bound
T = Temperature change (ΔT)	−1°C	+8°C
P = Precipitation change (ΔP)	−50%	+50%
CO_2 = Carbon dioxide concentration [CO_2]	330 ppm	900 ppm

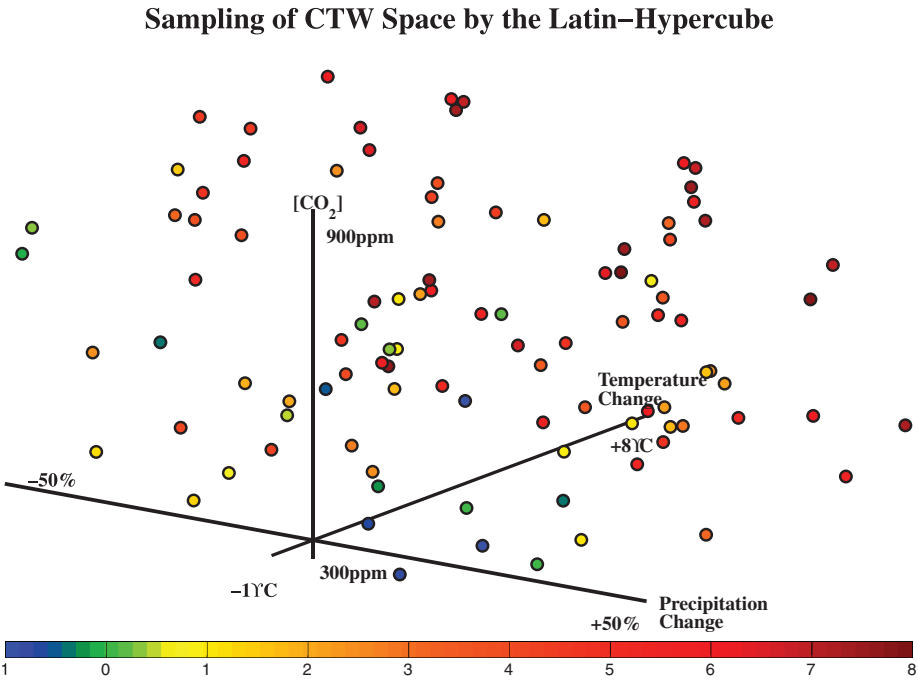


Fig. 2. Three-dimensional carbon dioxide concentration [CO_2], temperature, and water (CTW) uncertainty space. The points represent each of the 99 Latin Hypercube-generated sensitivity tests, which include a change in [CO_2], temperature, and precipitation based upon the ranges shown in Table 1. The colored bar also indicates the change in temperature, in order to illustrate the distribution of simulations better.

Furthermore, C3MP has extended these ranges slightly beyond the GCM-projected ranges so that contributed results will remain relevant in the event that more extreme projections become plausible (Fig. 2). In addition to the range of projected temperature increases, sensitivity tests also extend to a 1°C cooling in order to account for potentially optimal growing conditions, which may occur at temperatures cooler than the historical baseline. As the C3MP protocols require the same sensitivity tests for all crop modeling locations, the range of precipitation changes was limited to +/–50% to prevent the sensitivity tests being too sparse in the precipitation change uncertainty space, and so that we might accommodate more arid regions, where future projections could result in large percentage changes to small historical precipitation totals.

We note that changes in rainfall are restricted to changes in total amount, as precipitation variability is not yet considered in C3MP, although it is important in understanding yield response (Baigorria *et al.*, 2007). While in the highest representative concentration pathway (RCP8.5; Moss *et al.*, 2010), the final years of the 21st century have a [CO_2] higher than 900 ppm, the 30-year end-of-century time-slice

(2070–2099) has a central-year [CO_2] of 801 ppm. The 330 ppm lower limit of the [CO_2] range helps resolve CO_2 sensitivities around the 1980–2010 historical baseline's central year ([CO_2] in 1995 = 360 ppm).

The 99 sensitivity tests (shown in Table 2) were generated by using a Latin Hypercube sampling method, and include altered [CO_2] values and changes in temperature and precipitation that are applied to a baseline (1980–2009) daily weather series. A Latin Hypercube approach enables an evenly distributed and comprehensive sampling of a given uncertainty space, such as that specified by the CTW changes in Table 1. These [CO_2], temperature, and precipitation ranges are divided into 99 bins, and each bin is considered to be equally probable. A random value is then sampled from the first [CO_2], temperature-change, and precipitation-change bins, and these are combined to create "Sensitivity Test 1", which is applied to the baseline climate series for use in crop model simulations. The process is continued until all bins have been sampled for each CTW variable to form the 99 C3MP sensitivity tests, all of which are shown in Table 2, and are to be utilized by all participants. Figure 2 shows each of the 99 sensitivity tests plotted within the bounded CTW uncertainty space, and this demonstrates the relatively comprehensive sampling achieved using this method (a movable 3D image is available at www.agmip.org/c3mp). Ninety-nine tests were selected in order to facilitate crop model operation, and to obtain a large sampling of resultant yields without participants needing to perform numerous, successive model simulations.

To apply the sensitivity tests in crop model simulations, these CTW changes are implemented as an additive change in temperature (Table 2, column 2), a multiplicative change in precipitation (Table 2, column 4), and an imposed concentration of carbon dioxide [CO_2] (Table 2, column 5). For each sensitivity test, these temperature and precipitation changes are applied by directly modifying each day in the 1980–2009 daily climate time-series specific to the site being simulated. Repeating this process for each of the 99 sensitivity tests results in 2970 (99 tests × 30 years) yields per simulation.

The 30-year mean yield (Y) is then calculated for each sensitivity test. To understand how climate changes may affect yield variability, the coefficient of variation for yield across the 30 years (CV) is also calculated (Osborne and Wheeler, 2013). This enables the least-squares fitting of a quadratic crop model emulator for Y and CV for any given simulation location as a function of carbon dioxide concentration (CO_2), temperature change (T), and precipitation change (P) to determine coefficients a–k in each of the following equations:

$$\begin{aligned} Y(CO_2, T, P) = {} & a + b(T) + c(T)^2 + d(P) + e(P)^2 + f(CO_2) \\ & + g(CO_2)^2 + h(T^*P) + i(T^*CO_2) + j(P^*CO_2) \\ & + k(T^*P^*CO_2), \end{aligned} \tag{1}$$

Table 2. The 99 C3MP sensitivity tests.

Sensitivity test number	Change in temperature (°C)	Precipitation change (%)	Precipitation multiplier (fraction of baseline)	CO_2 concentration (ppm)
1	0.7	−17	0.83	418
2	0.0	23	1.23	458
3	1.9	−22	0.78	524
4	7.5	10	1.10	766
5	3.6	24	1.24	673
6	1.0	34	1.34	403
7	2.8	38	1.38	551
8	4.8	8	1.08	576
9	3.9	−42	0.58	700
10	4.3	−33	0.67	333
11	6.9	35	1.35	704
12	2.5	−12	0.88	875
13	5.4	15	1.15	377
14	0.2	27	1.27	777
15	2.1	3	1.03	714
16	6.5	−32	0.68	768
17	2.4	−48	0.52	510
18	7.8	26	1.26	607
19	4.2	−46	0.54	346
20	7.3	−28	0.72	544
21	7.1	−35	0.65	500
22	6.8	15	1.15	825
23	1.1	41	1.41	604
24	5.8	21	1.21	807
25	5.1	32	1.32	494
26	3.2	39	1.39	366
27	3.1	−40	0.60	732
28	7.9	−3	0.97	591
29	3.1	34	1.34	866
30	3.4	13	1.13	585
31	5.6	45	1.45	412
32	2.5	44	1.44	660
33	−0.1	−43	0.57	744
34	5.5	−9	0.91	572
35	4.0	−20	0.80	490
36	4.6	−38	0.62	839
37	6.3	−37	0.63	883
38	0.9	32	1.32	545
39	7.2	44	1.44	453
40	1.6	49	1.49	691
41	5.2	−13	0.87	454
42	2.0	−16	0.84	504
43	0.5	−7	0.93	537
44	4.7	−25	0.75	518

(*Continued*)

Table 2. (*Continued*)

Sensitivity test number	Change in temperature (°C)	Precipitation change (%)	Precipitation multiplier (fraction of baseline)	CO_2 concentration (ppm)
45	6.7	−11	0.89	486
46	1.3	−26	0.74	340
47	2.7	−11	0.89	424
48	5.9	−19	0.81	580
49	4.3	−9	0.91	793
50	−0.9	31	1.31	435
51	0.1	33	1.33	384
52	4.9	22	1.22	440
53	3.6	30	1.30	724
54	3.8	−5	0.95	836
55	6.4	4	1.04	642
56	6.3	11	1.11	433
57	1.4	−29	0.71	871
58	−0.2	11	1.11	475
59	7.0	−21	0.79	856
60	7.3	−24	0.76	829
61	4.5	−45	0.55	847
62	−0.3	−21	0.79	648
63	−0.5	5	1.05	629
64	0.6	47	1.47	861
65	−0.8	18	1.18	355
66	5.1	20	1.20	638
67	0.2	6	1.06	719
68	4.4	0	1.00	783
69	6.1	37	1.37	482
70	2.4	−6	0.94	399
71	6.6	−34	0.66	798
72	1.7	24	1.24	887
73	1.8	1	1.01	563
74	5.9	−16	0.84	898
75	3.5	19	1.19	526
76	1.2	−40	0.60	394
77	5.2	−50	0.50	554
78	0.4	9	1.09	679
79	7.2	14	1.14	727
80	0.9	7	1.07	663
81	−0.4	40	1.40	514
82	−0.6	12	1.12	426
83	5.7	−1	0.99	406
84	5.4	−44	0.56	754
85	5.5	21	1.21	621
86	7.6	−36	0.64	380
87	6.0	−27	0.73	444

(*Continued*)

Table 2. (*Continued*)

Sensitivity test number	Change in temperature (°C)	Precipitation change (%)	Precipitation multiplier (fraction of baseline)	CO_2 concentration (ppm)
88	2.7	2	1.02	815
89	7.5	0	1.00	645
90	−1.0	29	1.29	670
91	4.1	28	1.28	802
92	2.2	48	1.48	655
93	3.9	−35	0.65	689
94	1.7	43	1.43	587
95	0.3	−44	0.56	774
96	4.9	−47	0.53	709
97	6.2	17	1.17	852
98	2.2	39	1.39	599
99	1.1	6	1.06	737

and

$$CV(CO_2, T, P) = a' + b'(T) + c'(T)^2 + d'(P) + e'(P)^2 + f'(CO_2) + g'(CO_2)^2 + h'(T^*P) + i'(T^*CO_2) + j'(P^*CO_2) + k'(T^*P^*CO_2). \quad (2)$$

The emulators for mean yield and yield CV are fitted separately, and the values of coefficients $a-k$ in Equation 1 will not be the same as $a-k$ in Equation 2 (Ruane *et al.*, 2013b). Ruane *et al.* (2013b) utilized similar second-order polynomials to emulate impact-response surfaces for maize in Panama to represent peak yields under optimal conditions. These emulators define an impact-response surface that highlights the crop sensitivity to the specified CTW changes. The formulation of this crop model emulator is an important area of continuing research in C3MP, as it is possible that some locations' mean yield or yield CV responses may be better captured by polynomials of a different order or by using logarithmic functions.

The introduced cross-variable terms in Equations 1 and 2 are a unique feature of the C3MP emulators, which allow for non-orthogonal curvature in the crop response space that result from interactions between the CTW variables in crop models (Ruane *et al.*, 2014). Such terms can aid understanding of how CTW variables impact yields in combination (Sheehy *et al.*, 2006). In addition, Ramankutty *et al.* (2013) tested linear, non-linear, and spline fits for a grassland site in Australia, which could be repeated for any site participating in C3MP. Lobell and Burke (2010) performed a similar regression using crop model simulations of interannual variability, and found that quadratic regressions outperformed linear models, which lends further support to the C3MP approach. In the particular cases in which the above emulator does not fully capture a crop's response at a specific location, for instance in marginal

growing areas where the crop response may not be linear or quadratic, C3MP is working with participants to facilitate the development and use of additional or alternative emulators at those sites.

Climate data and information

To ensure consistency across sites and encourage the contribution of crop modeling simulations from regions where climate information does not exist or is not available, C3MP provides an estimated daily climate time-series for the 1980–2010 historical baseline period. Based on the outputs of the NASA Modern Era Retrospective-Analysis for Research and Applications (MERRA; Rienecker *et al.*, 2010), MERRA-Land (Reichle *et al.*, 2011) outputs and NASA-GEWEX Solar Radiation Budget daily radiation data (Zhang *et al.*, 2007), these AgMERRA data were developed for agricultural impacts applications and are adjusted to eliminate apparent monthly biases in comparison to an ensemble of gridded observational data from weather stations and satellites (Ruane *et al.*, 2014, and references therein).

Some participants may have access to complete (i.e., with no gaps, missing years, or spurious values) 1980–2010 observed historical climate datasets that are also publicly available. In such cases, participants are encouraged to apply the 99 sensitivity tests to these observed datasets and perform their C3MP crop model simulations while also conducting the simulations with AgMERRA data, to enable location-specific comparisons. Simulations using both observed and AgMERRA-based weather can be submitted to the C3MP database, and the crop impacts are investigated by using the emulator approach described above.

Participating in C3MP

To participate, prospective contributors register their interest at https://www.agmip.org/c3mp-registration/ and complete a C3MP questionnaire, which provides supplementary material and information to C3MP coordination regarding the proposed simulations. For each of their proposed simulation contributions, participants provide the following information and details:

- Simulation location (latitude, longitude, and elevation).
- Public availability of weather data.
- Crop species, cultivar, water regime, and any other relevant crop information.
- Planting and harvest months.
- Crop model version and components.
- Nitrogen application (approximate amount).
- Soil-profile source, including relevant references.
- Calibration procedures, including relevant references.
- Reference to a previous study that uses the specified model and information.

The above details must be provided for each new simulation, as these constitute a unique simulation set. For example, some participants have simulated the same crop/location multiple times with an identical model setup, but varying only the amount of nitrogen applied. These are considered separate, unique simulations sets based upon the varying nitrogen levels.

Upon completion and submission of the questionnaire that describes the simulations sets, C3MP provides participants with a 30-year (1980–2009) AgMERRA daily weather time-series, based on their specified latitude and longitude, along with the 99 sensitivity test parameters (Table 2) needed to complete the C3MP simulations. Once the sensitivity simulations are completed, participants are given an Excel-based results reporting template (available at http://www.agmip.org/c3mp-downloads/) that is designed to help format their crop yield results for entry into the C3MP database. Multiple simulations sets may be reported by using the results reporting template. When completed participants email the file to C3MP coordination for processing and archiving. There is currently no limit on the number of simulation sets, sites, crops, and models that any one participant can contribute, and all participants are encouraged to submit as many site-calibrated simulations as they are able.

C3MP recent developments and updates

Since launching in February 2013, C3MP has received well over 1000 simulated results using the above-described methodology, and additional and new results are contributed regularly. Efforts are underway to create and improve a C3MP networking platform, expand and evaluate contributed results through a comprehensive database, and develop a range of climate-crop analyses for distribution and feedback. A major advance has been the release of the entire C3MP contributions archive and results database via a secure, online "C3MP Research" platform, which is accessible to, and benefits, all participants who have contributed simulated results. Contributors are now able to access all the C3MP submissions to date, and also have access to various analysis tools in development by C3MP Coordination Team, which will facilitate further various studies and collaborations.

Another major task C3MP has undertaken is to evaluate and vet the contributed results of Phase 1. Preliminary assessments are presented below to demonstrate how representative the C3MP emulator and approach are with respect to the submitted simulations. Additional checks and evaluations will be pursued as Phase 1 analyses continue.

C3MP is also identifying areas for improvement of the protocols, and additional information needed from participants to understand and analyze the submitted results. These improvements and methodological adjustments are discussed below, and will be incorporated in C3MP Phase 2.

Furthermore, the C3MP Research site also hosts a C3MP forum, in which contributors are invited to post questions, discuss results, and explore avenues for collaboration. The forum is a utility that further expands and strengthens the global network of crop modelers, particularly for coordinated crop model assessments. The current, detailed C3MP protocols are freely available at http://www.agmip.org/c3mp-downloads/. More information about the project and registration can be found at www.agmip.org/c3mp.

C3MP participation to date: Coverage and scope

C3MP currently benefits from contributions covering over 18 crops (Table 3), over 56 countries (Table 4), and 23 crop models (Table 5). Figure 3 shows major global cropped areas (green regions, Monfreda *et al.*, 2008), with all contributed C3MP sites superimposed (red dots).

Table 3 shows the diversity of crops that have been simulated and contributed for C3MP Phase 1. The majority of the submitted results simulate yields for the major global commodities: wheat, rice, maize, and soybean, with the number of contributions of these crops' simulations increasing across the globe. However, C3MP has also received simulations for less-frequently modeled crops, such as grapevine, sunflower, and even Bambara groundnut, an indigenous variety found in West Africa

Table 3. Crop distribution of contributed C3MP simulations.

Crop	Number	Percent
Bambara groundnut	2	0.17
Barley	10	0.87
Canola	3	0.26
Chickpea	3	0.26
Cotton	2	0.17
Grapevine	1	0.09
Lentil	1	0.09
Maize	291	25.35
Millet	75	6.53
Pasture	39	3.40
Peanut	29	2.53
Potato	10	0.87
Rice	119	10.37
Rye	2	0.17
Sorghum	14	1.22
Soybeans	184	16.03
Sugarcane	13	1.13
Wheat	350	30.49

Table 4. Country distribution of contributed C3MP simulations.

Country	Number	Percentage	Country	Number	Percentage
Argentina	49	4.5	Japan	9	0.8
Australia	27	2.5	Kazakhstan	11	1
Austria	8	0.7	Lithuania	2	0.2
Bangladesh	48	4.4	Madagascar	1	0.1
Belarus	8	0.7	Malawi	4	0.4
Belgium	7	0.6	Mali	8	0.7
Benin	2	0.2	Mauritania	4	0.4
Bolivia	18	1.6	Mexico	3	0.3
Botswana	2	0.2	New Zealand	20	1.8
Brazil	27	2.5	Niger	10	0.9
Burkina Faso	12	1.1	Pakistan	11	1
Cameroon	1	0.1	Panama	4	0.4
Canada	8	0.7	Philippines	6	0.5
China	63	5.7	Poland	3	0.3
Czech Republic	4	0.4	Republic of Korea	8	0.7
Denmark	7	0.6	Russia	16	1.5
Egypt	7	0.6	Senegal	19	1.7
Finland	1	0.1	South Africa	6	0.5
France	6	0.5	Spain	12	1.1
Germany	3	0.3	Sri Lanka	35	3.2
Ghana	8	0.7	Thailand	7	0.6
Greece	12	1.1	The Gambia	6	0.5
Guinea	2	0.2	The Netherlands	5	0.5
Guinea-Bissau	6	0.5	Togo	2	0.2
India	42	3.8	Ukraine	17	1.5
Indonesia	5	0.5	United Kingdom	2	0.2
Iran	9	0.8	United States	459	41.8
Italy	16	1.5			

(Karunaratne *et al.*, 2011). All crops are encouraged, and C3MP welcomes the modeling of both major and minor crops at diverse sites in order to facilitate a range of analyses of these crops' sensitivity to climate change.

Nearly 42% of the contributed sites are from the US (Table 4), facilitated by the US's extensive crop modeling network, but the number of countries from which sites have been contributed is growing. The crop coverage obtained in Phase 1 represents many agricultural regions, but C3MP has also identified those regions where gaps in coverage exist, such as the Middle East, Mesoamerica, East Africa, and Southeast Asia, and is actively recruiting participants to contribute crops/sites in these gap regions. In particular, representation is needed from developing countries, marginal regions that might display significantly different crop responses, and also those regions that are expected to be the most vulnerable to future climatic changes (such as those regions that are already affected by sea-level rise and other indirect

Table 5. Crop model distribution of contributed C3MP simulations.

Crop	Number	Percentage
APSIM	69	6.3
AquaCROP	7	0.6
CropSyst	20	1.8
DailyDaycent	4	0.4
DRAINMOD-DSSAT	1	0.1
DSSAT	872	79.4
Fasset	1	0.1
GLAM	1	0.1
InfoCrop	11	1
Lintul	2	0.2
MCWLA	3	0.3
RZWQM	2	0.2
RZWQM-DSSAT	4	0.4
SARRA-H	70	6.4
Sirius Quality	13	1.2
SPRiGS	1	0.1
SSM	9	0.8
STICS	7	0.6
VITE model	1	0.1

forcings). Additionally, C3MP encourages existing participants in each country to submit additional sites, and to engage with new participants by leveraging the global C3MP network of crop modelers.

A majority of the submitted simulation sets was performed with the Decision Support System for Agrotechnology Transfer (DSSAT, Hoogenboom *et al.*, 2012, see Table 5). The DSSAT modeling community is well integrated, and has a particularly strong network with which to disseminate information regarding C3MP participation and other initiatives, with the assurance that such information will reach most of the community. DSSAT also provides a means by which to rapidly and efficiently modify weather-related crop model inputs, via adjustment of the "environmental modifications" in the crop model simulation setup (Jones *et al.*, 2003; Hoogenboom *et al.*, 2012). C3MP has created a template based on the syntax of these environmental modifications, which DSSAT users may download and utilize to rapidly execute their 99 sensitivity simulations. For these reasons, a majority of contributed results were simulated by using DSSAT model versions.

Similar to the DSSAT environmental modifications template, C3MP has also created a similar tool for the Agricultural Production Systems Simulator (APSIM, Keating *et al.*, 2003) to apply more easily the sensitivity tests to climate data for APSIM crop model simulations. The tools are contained in a downloadable package

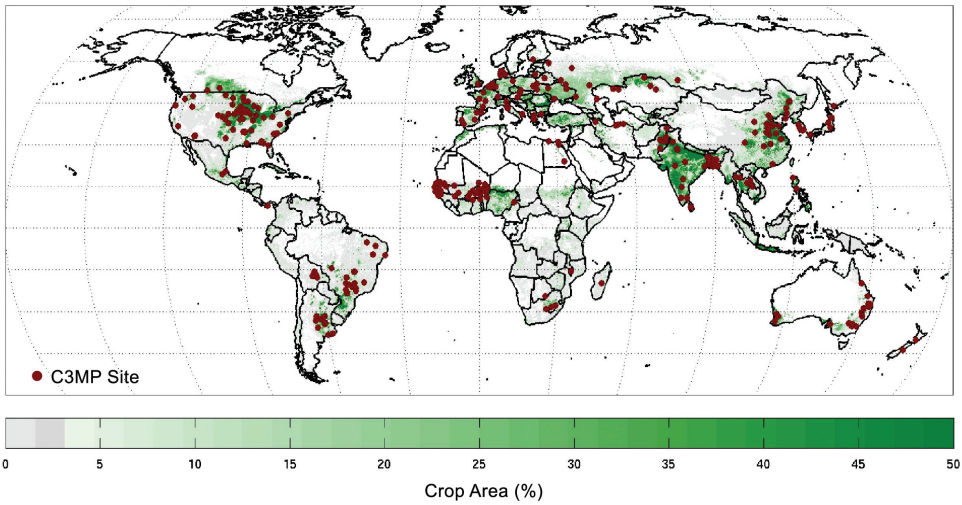


Fig. 3. Major cropped areas (green, Monfreda *et al.*, 2008) and C3MP contributed sites (red dots).

on the C3MP downloads page (www.agmip.org/c3mp/downloads), and have enabled more APSIM users to contribute to these coordinated experiments in a streamlined, efficient manner. Likewise, C3MP is making a dedicated effort to create tools for other modeling platforms, such as the French National Research Institute for Agricultural Research STICS crop growth model (Brisson *et al.*, 2003; Ripoche, personal communication), which will enable fast and efficient contributions from these communities. C3MP is also working to broaden communications and reach other crop modeling communities by identifying listserves, presenting C3MP at international conferences, and soliciting individuals and groups of model users. Additionally, C3MP has recently engaged the international livestock and pasture modeling community to contribute results (Snow *et al.*, 2014).

The C3MP Database and Evaluation

The C3MP database: Access and tools

The C3MP database was made exclusively available to active C3MP contributors in January 2014. This database will be released in phases over the duration of the project, enabling and facilitating collaborations and the undertaking of additional studies through the C3MP Research website. The C3MP database will be open for public access in January 2015, which corresponds to Phase 2 of the project; however the Research website will remain accessible to project contributors only. Research website users are able to access all emulated results at each site, any

figures, analyses, and/or impacts response surfaces (Ruane *et al.*, 2014) generated at each site, a comprehensive metadata file that details the specifications for each simulation, a forum where questions and comments can be exchanged, and a host of tools that will aid in the analysis and interpretation of results. In addition, the emulator coefficients that were obtained for each simulation are also made available to enable further analysis and discussion. Each simulated set of results posted on the research website has been assigned a unique four-digit identification number which can be used to determine the metadata for each set (e.g., location, crop, crop model, irrigation, etc.) Downloadable AgMERRA daily climate time-series over the 1980–2010 time-period are also provided for each of the simulated locations. This provides the C3MP community with all of the data necessary to conduct climate assessments on the submitted results. The site is continuously updated as more submissions are contributed.

C3MP is actively constructing and adding to a tool-shed that is available via the C3MP research site. A number of tools have been created to facilitate contributors' crop model simulations, to make the submitted and emulated results easily accessible, and to enable collaborative research within the C3MP community. One such tool is a downloadable package containing an executable program designed to apply the 99 sensitivity tests to weather datasets in an APSIM-compatible format, which eases the completion of the necessary C3MP simulations for APSIM users. C3MP coordination is in the process of creating a similar tool for contributors who model crops by using STICS, and will be interacting with other modeling communities to identify ways to make the application of the C3MP protocols simple and efficient. It is also likely that individual participants may have, or will, create their own tools to execute the sensitivity tests (or perform various analyses for their crops/sites). In these cases, C3MP encourages participants to share their simulation tools, and will facilitate the connection of participants and distribution of these tools, while establishing proper credits and attribution.

C3MP coordination team has also made available an "Emulator Calculator" tool, which allows participants to determine quickly the emulated mean yields and yield coefficients of variation (CV) of up to 20 user-specified simulation sets (Fig. 4). This calculator is defined by the emulator equation discussed above (Ruane *et al.*, 2014). The user first enters the climate variable values (temperature, precipitation, and $[CO_2]$) to be emulated by the calculator, followed by the four-digit code for the simulations of interest (up to 20). After setting these parameters, the calculator displays the emulated baseline (where $\Delta T = 0°C$, $\Delta P = 0\%$, and $[CO_2] = 360$ ppm) and emulated values as determined by the user-defined climate variables for both mean yield and yield CV. The calculator also shows the percent change from the baseline scenario of the user-defined emulation for mean yield and yield CV.

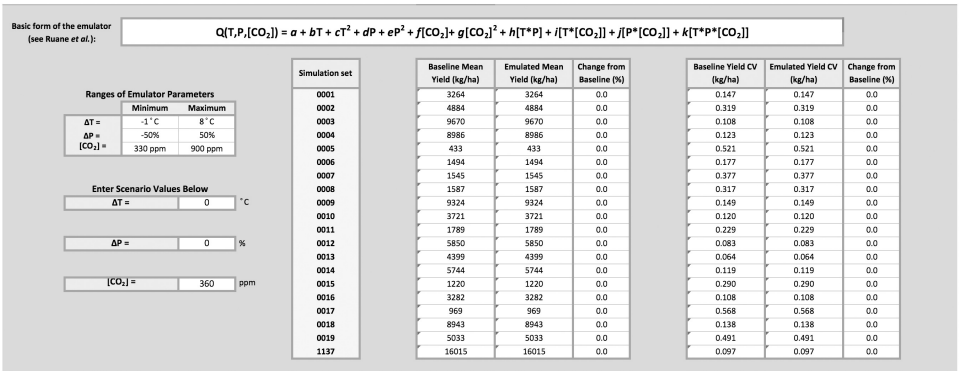


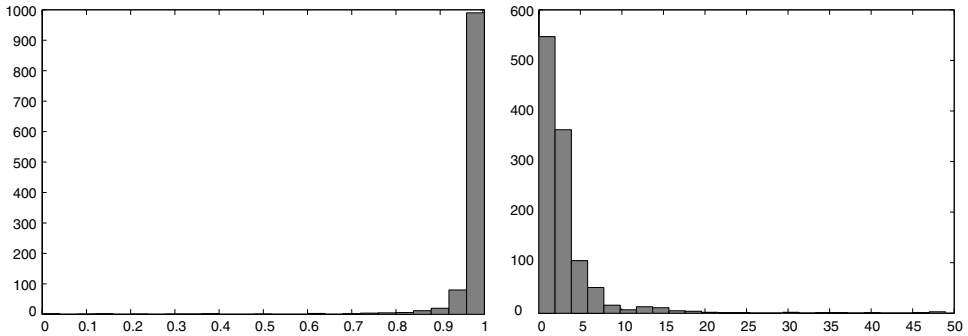
Fig. 4. Screenshot of the "Emulator Calculator". This tool allows the user to view the emulated mean yield and yield CV of 20 user-selected simulation sets. The user can adjust the climate parameters to change the emulated mean and CV. The emulated baseline (where temperature change is 0°C, precipitation change is 0%, and atmospheric carbon dioxide concentration is 360 ppm) is always shown for the selected simulation sets, as is the percentage change of the user-defined emulation from the emulated baseline values.

Lastly, the C3MP Research website has developed an online message board to act as a forum for the community. This online forum allows C3MP Coordination to inform the community of changes and updates to the datasets while notifying the community of new tools and other upcoming events related to C3MP. The message board encourages discussion between contributors, provides opportunities for greater collaboration on ongoing research efforts, and maintains a public space for posting figures and other research results.

Evaluating the fit of emulated responses

A major objective of Phase 1 is to evaluate the efficacy of the C3MP emulator to capture yield responses for the wide array of potential carbon dioxide, temperature, and water (CTW) changes, and to assess C3MP's overall methodology and ability to serve the analysis needs of the global crop modeling community. As an initial assessment, the r^2 correlation coefficient and the root-mean-square error (RMSE) are presented for the comparison of the C3MP emulated results to the crop model simulated yields at each of the 1100+ existing C3MP sites (Fig. 5). For a large majority of the contributed sites, the emulator displays an $r^2 > 0.95$ and an RMSE $< 5\%$, which suggests that for most contributed locations, the described C3MP emulator does well to capture the major modeled crop–climate interactions and CTW responses.

However, there are sites where the C3MP emulator does not display a completely representative fit to the simulated results. C3MP coordination is currently identifying these sites and interacting with the respective contributors to understand and attribute the differences between the emulated and simulated results. The emulator



(a) r^2 correlation for Emulator Fit (b) RMSE for Emulator Fit

Fig. 5. Correlation and RMSE for emulator fit to 1000+ C3MP contributed simulations.

terms may not sufficiently characterize all the important CTW interactions that occur at some unique sites. In these cases, C3MP is engaging with contributors to develop emulators that better represent these specific crops/sites and crop sensitivities to CTW changes.

Quality assessment and quality control

C3MP is also currently investigating the general patterns of specific crops' responses that are emerging globally and regionally from the contributed simulation sets, and identifying locations that appear to have anomalous responses relative to similar, nearby locations. As an example, Fig. 6 shows all the contributed simulation sets for rainfed maize. Although more sites are needed to ascertain a global response pattern confidently, these initial contributions generally indicate that a 4°C increase in temperature, and declines in rainfall of 25% can adversely impact yields; this is a consistent response across the sites. Increases in [CO_2] to 720 ppm (keeping temperature and rainfall at current conditions) result in slightly positive crop yield responses, particularly at higher latitudes and across North America. While these results appear to be fairly consistent across the sites, there are locations where the response differs from neighboring sites, and in these cases, the anomalous response is flagged for further scrutiny.

C3MP has encouraged participants to submit simulated yields for the same site using a variety of input parameters (such as N applications) to allow future intercomparison. This has occasionally led to instances in which the modelers were attempting to simulate yields of crops at sites where these crops are unviable, or to impose rainfed water-management strategies in locations heavily reliant upon irrigation. The latter is illustrated, for example, for rainfed maize by low baseline emulated yields (Fig. 6a) and a largely positive response to a 4°C temperature increase (Fig. 6b) in

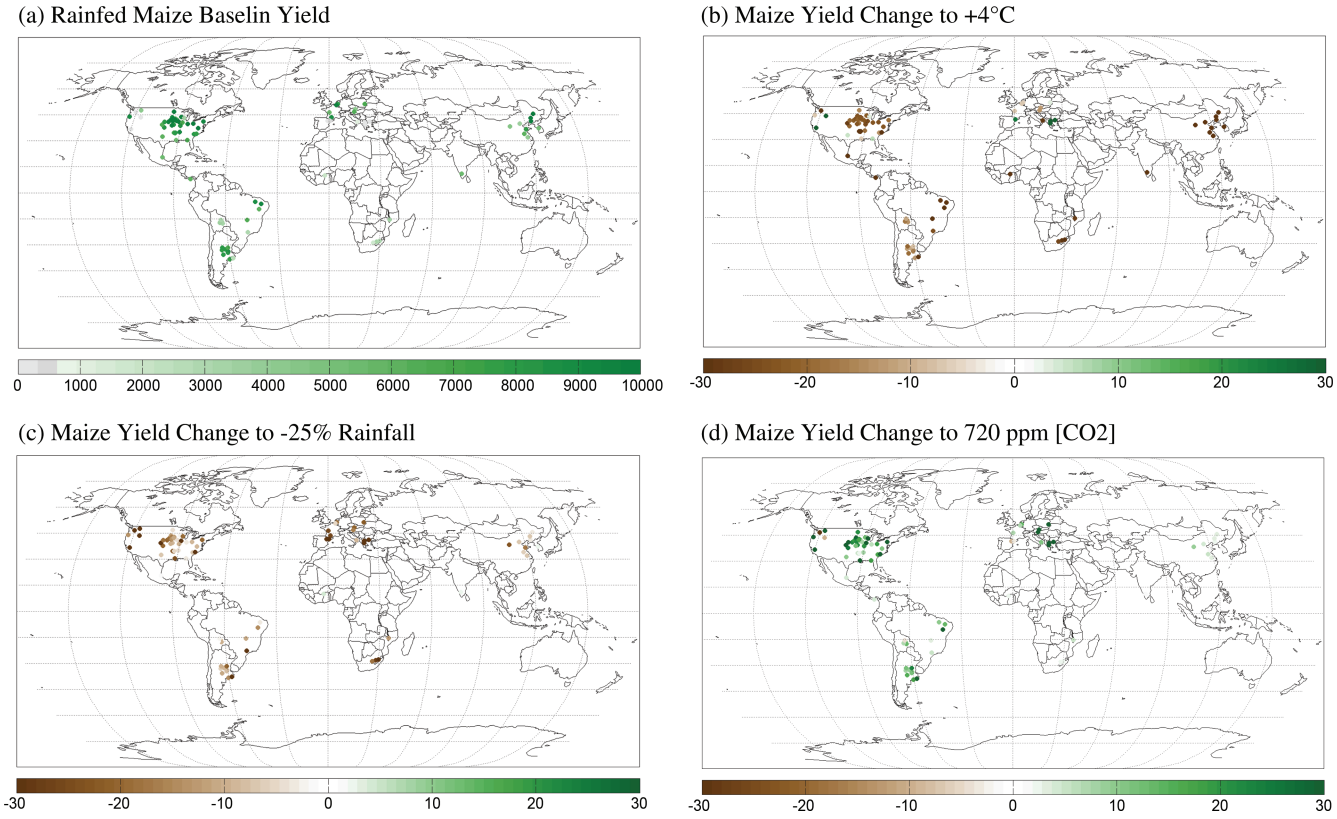


Fig. 6. (a) Baseline yield for rainfed maize, and (b, c, d) rainfed maize: 4°C increase in temperature, 25% decrease in rainfall, and 720 ppm [CO_2], respectively.

the northwest USA, which are actually irrigated sites. Such simulations prove difficult to accurately emulate, and, in some cases such as the northwest US, may not be representative of site-specific practices or conditions that allow the crop to be viable.

C3MP has indicated such anomalous crop responses with a "flag" in the simulation database available currently to active contributors. Contributors are encouraged to help diagnose and investigate the causes of incongruity, thereby harnessing the collective expertise of the global crop modeling community. These analyses and contributor interactions can help to catch unintended errors in simulations, and assess the best or most suitable site-specific conditions and management for current crop viability. Establishing the site-specific conditions of current crop viability will also lead to more accurate and informative future climate impacts assessments at that site. Such participant-led evaluations will further provide more robust assessments of crop model differences and identify areas of potential model improvement and refinements in model calibration.

C3MP Phase 1: Lessons Learned and Initial Findings

Lessons learned

In Phase 1, C3MP endeavored to obtain a sufficient amount of simulation information from contributors, while minimizing their time and effort commitment. However, as C3MP begins to evaluate and understand the variety of crop, location, and model responses to carbon dioxide, temperature, and water (CTW) changes, the coordination has identified additional pieces of information that prove important in evaluating the contributed results.

C3MP had originally decided not to ask for simulated baseline yield values, in order to allow participants to retain ownership of their crop model configuration. However, the baseline yields do provide crucial context for emulator validation, and could enable other assessments that add to the richness and utility of the project. A baseline simulation, and the contribution of baseline yields, is relatively simple to perform and computationally inexpensive. C3MP will request this additional baseline simulated yield information in Phase 2, and will make every effort to maintain and accredit participants' ownership of their crop model setup.

Additionally, C3MP had requested the average planting and harvest months for archival and metadata purposes, but there is much interest in understanding how the yearly planting and harvest dates may change with climate change. Therefore, in Phase 2, C3MP will also ask for the yearly planting and harvest dates. This will also allow for better identification of sources of variability, isolation of the year-to-year crop response during the prime growing season, and can enable a number of analyses across crops and regions, such as the impact and/or avoidance of drought or frost

conditions. In some crop models, a failure to mature in one year can allow the plant to carry-over and mature the following year, which leads to some inconsistencies in the yearly harvest dates. This can be better identified if the yearly information is collected and assessed.

Findings and analyses

The C3MP coordination team has identified some general responses that warrant further explanation and interaction with the greater community of collaborators. Firstly, crop model calibrations may be achieved with respect to the optimal temperature for the specific crop/cultivar at a particular site. However, in the responses for many major crops across numerous simulations, small changes in temperature from the baseline result in yield improvements, before deteriorating under greater temperature changes. This would suggest that some of the models were not necessarily calibrated for the optimal crop growth temperature at these locations. Additional work by the C3MP and field experimenter community could aid in deeper understanding of the crop response to small temperature changes.

Secondly, C3MP is continuing assessments of the crop impact response surfaces generated for each simulation set. Ruane *et al.* (2014) illustrates a prototype C3MP analysis for peanut in Henry County, Alabama, and describes the crop impact response surface, which is taken at the zero-change cross-sections of the CTW uncertainty space. These response surfaces can also be constructed for the mean peanut response (or any crop in the C3MP database) across multiple locations. For example, results have also been contributed for peanut simulations from locations in India, Ghana, Thailand, and additional sites in the US. Many aspects of these simulations and model calibration differ across the sites, which makes direct comparison between simulation sets challenging. However, as participation grows, C3MP anticipates large increases in the number of contributed sites for each crop, which can enable a variety of analyses. Participants will have the ability to access all contributed simulation-set results to understand their crop response within the context of the mean response across all locations or a selected subset of the submitted simulations. This will allow participants to compare their results to those of the larger research community.

Thirdly, C3MP has also identified multiple simulations sets that are either co-located or are characterized by similar climates (i.e., similar temperature and rainfall), but display largely disparate mean yield values between different crop models. This may be attributed to many factors, including differing soils, cultivars, fertilizer applications, management, etc. There may also be mean yield biases between models that are being investigated by AgMIP Crop Teams (Asseng *et al.*, 2013; Bassu *et al.*, 2014; Li *et al.*, 2014; Singels *et al.*, 2013), and also warrant

further investigation by the greater C3MP community, particularly participants who are using different crop models to simulate similar environmental conditions. For the purposes of near-term investigations and analyses, C3MP will focus on the yield responses (percent change and change in CV), rather than the absolute mean yields.

C3MP is actively working both to integrate the lessons learned in the updated protocols for Phase 2 of the project, and also to understand and share these and other recent findings. Continuous interactions with the greater C3MP community can help to prioritize and organize these activities, and create new opportunities for study and evaluation.

Continuing C3MP Efforts and Future Work

C3MP will review all contributed simulation sets and work with participants to rectify and/or explain any discrepancies between simulated and emulated values, or anomalous results. As the database of contributed sites continues to grow and improve in quality, C3MP has identified major analyses that can be performed at any location and pursued for publication. These include, but are not limited to:

- *Analyses of current sensitivity*: By examining the slope of the emulated response surfaces at the historical baseline climate's location ($\Delta T = 0°C$; $\Delta P = 0\%$; [CO2] = 360 ppm), it is possible to examine the sensitivity of yield to each climate variable. Simulation sites where immediate sensitivity and potential for damages are high can be highlighted in regard to climate risks and vulnerability.
- *Climate change analyses (including CMIP5 GCMs)*: Emulated impact response surfaces also facilitate assessments of projected climate impacts on a given region and crop. By examining CMIP5 GCM outputs that correspond to simulation-site locations, distributions of projected changes in growing season temperature and precipitation can be determined and coupled with [CO_2] values from the corresponding representative concentration pathway (Moss *et al.*, 2010) for any given time-slice. These projections may then be used to calculate probabilistic yield-change estimates by using the emulated response surfaces. A similar approach would also be possible with other climate model ensembles, in addition to data from various downscaling approaches or scenario-generation techniques.
- *Exploring uncertainties by using the network of C3MP locations*: In addition to climate vulnerability analyses, C3MP will generate maps of crop modeling simulation locations that can be used to build the network of AgMIP sites and crop modelers around the world to facilitate comparison and collaboration in future studies. Such comparisons and crop response evaluations at multiple sites can also allow detailed investigations of model and crop response uncertainty, which may be characterized across models, geographic areas, and other factors.

- *Regional-based analysis*: If enough simulation sites are contributed for a particular region (e.g., southeast South America), it may become possible for C3MP participants to undertake a more detailed investigation of that region. Such regional analyses include comparisons of simulation-set coverage relative to major agricultural regions, assessments examining the relative impacts of climate change on different subregions, or evaluations of the implications of updated climate scenarios or downscaled datasets on a particular region.
- *Crop-based analysis*: Similarly, if enough simulation sites are contributed for a particular crop (e.g., sorghum), it will become possible for C3MP participants to undertake a more detailed investigation of C3MP results for that particular crop. Possible areas of investigation include a comparison of the global coverage of the crop model simulations relative to the crop's major growing regions, an evaluation of the crop models that are employed that also compares model similarities and differences, and the interactions between the crop response and other environmental factors that distinguish particular simulations. The global community of modelers for each crop that has contributed to C3MP is highly encouraged to undertake and lead these assessments. Discussion may be easily facilitated via the C3MP Research website and forum.
- *Crop model-based analysis*: Finally, if a sufficient number of simulated sites are contributed for a particular crop model (e.g., APSIM, STICS, etc.), it may become possible for C3MP participants to undertake a more detailed investigation of C3MP results for that crop model. Potential areas of study may include the lessons learned about the sensitivity of the crop model to key climate change factors. Furthermore, efforts are underway by AgGRID (Rosenzweig *et al.*, 2014; see also Part 1, Chapter 7 in this volume) to execute the C3MP sensitivity tests for various global gridded crop models. Though direct comparisons with the C3MP results submitted from point-based crop models are challenging, the consistency between these and the global gridded model C3MP results can provide insight into broad, regional, and global crop responses and patterns to CTW changes. A large network of C3MP point-based simulations can also aid AgGRID model development, by providing a potential means for evaluating their spatial performance (if not a true model validation).

C3MP regional, crop-specific, and crop model analyses hold great potential for thorough analyses and motivate more detailed follow-on studies. Participants are invited to design extensions and analyses and ideas and discussion are welcomed via c3mp@agmip.org.

C3MP will continue to welcome more participants, accept additional results from existing or new members, vet and evaluate the existing contributions, refine the emulator approach for various sites, and expand participation among additional crop

modeling teams, and encourage coverage by modelers of under-represented countries and regions. C3MP will work to identify opportunities for collaboration among participants and coordinate publications and studies. Registration is and will remain open at www.agmip.org/c3mp. Interested parties may contact c3mp@agmip.org at any time for further information on how to contribute to this unique and rigorous global research effort.

Frequently Asked Questions (FAQs)

— Do I have to run other groups' sites?
C3MP: No. Participants will only simulate their own sites.

— Can I only run a site if it corresponds to a detailed field-trial experiment?
C3MP: No. Multiple sites can utilize the same management and cultivars if they are reasonable representations of local practices.

— What defines a unique C3MP site?
C3MP: A C3MP site is unique if it has unique climate, soil, management, or cultivar.

— What is the minimum number of sites that I'd have to run in order to participate?
C3MP: One. We welcome contributions of any size.

— Do I have to submit simulation-set configuration files and all inputs and outputs?
C3MP: No. Participants will complete a questionnaire that provides C3MP with the basic information about each of your simulations. Upon submission of the questionnaire, C3MP will send further instructions on how to run the sensitivity tests as well as a results reporting template to standardize the results submissions.

— Will I receive credit for my contributions?
C3MP: Yes. Participants will be co-authors on coordinated C3MP publications and will get access to the full C3MP archive for coordinated research activities prior to its full public release. Each dataset will also be associated with its authors in order to facilitate future collaborations and data exchanges.

— Is C3MP going to be used as a basis for detailed intercomparison of crop models?
C3MP: Not in Phase 1. C3MP's diverse model configurations limit systematic intercomparison of crop models. C3MP multi-model analysis will be limited to identifying consistency or inconsistency across models in a given region in order to motivate more detailed analysis, and potential targeted intercomparisons, as the project progresses.

References

Asseng, S., Ewert, F., Rosenzweig, C. Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Baigorria, G. A., Jones, J. W., Shin, D. W., Mishra, A., and O'Brien, J. J. (2007). Assessing uncertainties in crop model simulations using daily bias-corrected regional circulation model outputs, *Clim. Res.*, **34**, 211–222.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K. J., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A. R., Kersebaum, K. C., Kim, S.-H., Kumar, N. S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M. V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., and Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors?, *Global Change Biol.*, **20**(7), 2301–2320.

Bernsten J., Petersen, B. M., Jacobsen, B. H., Olesen, J. E., and Hutchings N. J. (2003). Evaluating nitrogen taxation scenarios using the dynamic whole farm simulation model FASSET, *Agricultural Systems*, **76**, 817–839.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussiere, F., Cabidoche, Y. M., Cellier, P., Debaeke, P., Gaudillere, J. P., Henault, C., Maraux, F., Seguin, B., and Sinoquet, H. (2003). An overview of the crop model STICS, *Eur. J. Agron.*, **13**(3–4), 309–332.

Challinor, A. J., Wheeler, T. R., Slingo, J. M., P., Craufurd, Q., and Grimes, D. I. F. (2004). Design and optimisation of a large-area process-based model for annual crops, *Agricultural and Forest Meteorology*, **124**(1–2), 99–120.

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S. (2012). Communication of the role of natural variability in future North American climate, *Nature Climate Change*, **2**, 775–779.

Freer, M., Moore, A. D., and Donnelly, J. R. (1997). GRAZPLAN: Decision support systems for Australian grazing enterprises. II The animal biology model for feed intake, production and reproduction and the GrazFeed DSS, *Agricultural Systems*, **54**, 77–126.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J. (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Jones, J. W, Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *European Journal of Agronomy*, **18**, 235–265.

Karunaratne, A. S., Azam-Ali, S. N., Al-Shareef, I., Sesay, A., Jorgensen, S. T., and Crout, N. M. J. (2011). Modelling the canopy development of bambara groundnut, *Agricultural and Forest Meteorology*, **150**, 1007–1015.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Roberston, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R.

L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**, 267–288.

Li, T., Hasegawa, T., Yin, X., Zhu, Y., Boote, K., Adam, M., Buis, S., Confalonieri, R., Fumoto, T., Gaydon, D., Marcaida, M., Oriol, P., Ruane, A. C., Ruget, F., Singh, B., Singh, U., Tang, L., Tao, L., Yoshida, H., Zhang, Z., and Bouma, B. (2014). Crop-model ensembles reduce uncertainty in predicting rice yield under climate change, *Proc. Roy. Soc. B: Biol. Sci.*, doi: 10.1111/gcb.12758.

Lobell, D. B. and Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change, *Agric. Forest Meteorol.*, **150**, 1443–1452.

Monfreda, C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, *Global Biogeochem. Cycles*, **22**, GB1022.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**, 747–756.

Negm, L. M., Youssef, M. A., Skaggs, R.W., Chescheir, G. M., and Jones, J. (2014). DRAINMOD-DSSAT model for simulating hydrology, soil carbon and nitrogen dynamics, and crop growth for drained crop land, *Agricultural Water Management*, **137**, 30–45.

Osborne, T. M. and Wheeler, T. R. (2013). Evidence for a climate signal in trends of global crop yield variability over the past 50 years, *Environ. Res. Lett.*, **8**, 024001.

Parton, W. J., Hartman, M. D., Ojima, D. S., and Schimel, D. S. (1998). DAYCENT: Its land surface submodel: Description and testing, *Glob. Planet. Chang.*, **19**, 35–48.

Ramankutty, P., Ryan, M., Lawes, R., Speijers, J., and Renton, M. (2013). Statistical emulators of a plant growth simulation model, *Clim. Res.*, **55**, 253–265.

Reichle, R. H., Koster, R. D., De Lannoy, G. J. M., Forman, B. A., Liu, Q., Mahanama, S. P. P., and Toure, A. (2011). Assessment and enhancement of MERRA land surface hydrology estimates, *J. Clim.*, **24**, 6322–6338.

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M. G., Schubert, S. D., Takacs, L., Kim, G. K., Bloom, S., Chen, J. Y., Collins, D., Conaty, A., da Silva, A., Gu, W., Joiner, J., Koster, R. D., Lucchesi, R., Molod, A., Owens, T., Pawson, S., Pegion, P., Redder, C. R., Reichle, R., Robertson, F. R., Ruddick, A. G., Sienkiewicz, M., and Woollen, J. (2011). MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, *J. Clim.*, **24**, 3624–3648.

Ritchie, J. T. (1972). Model for predicting evaporation from a row crop with incomplete cover, *Water Resour. Res.*, **8**(5) 1204–1213.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Rötter, R. P., Carter, T. R., Olesen, J. E., and Porter J. R. (2011). Crop-climate models need an overhaul, *Nature Climate Change*, **1**, 175–177.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014). AgMIP climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agric. Forest Meteorol.*, **200**.

Ruane, A. C., Cecil, L. D., Horton, R. M., Gordón, R., McCollum, R., Brown, D., Killough, B., Goldberg, R., Greeley, A. P., and Rosenzweig, C. (2013a). Climate change impact uncertainties for maize in Panama: Farm information, climate projections, and yield sensitivities, *Agric. For. Meteorol.*, **170**, 132–145.

Ruane, A. C., McDermid, S., Rosenzweig, C., Baigorra, G. A., Jones, J. W., Romero, C. C., and Cecil, L. D. (2013b). Carbon–Temperature–Water change analysis for peanut production under climate change: A prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP), *Global Change Biol.*, **20**, 394–407.

Sheehy, J. E., Mitchell, P. L., and Ferrer, A. B. (2006). Decline in rice grain yields with temperature: Models and correlations can give different estimates, *Field Crops Res.*, **98**, 151–156.

Singels, A., Jones, M., Marin, F., Ruane, A. C., and Thorburn, P. (2013). Predicting climate change impacts on sugarcane production at sites in Australia, Brazil and South Africa using the Canegro model, *Proc. Int. Soc. Sugar Cane Technol.*, **28**, 14.

Snow, V. O., Rotz, C. A., Moore, A. D., Martin-Clouaire, R., Johnson, I. R., Hutchings, N. J., and Eckard, R. J. (2014). The challenges — and some solutions — to process-based modeling of grazed agricultural systems, *Environ. Model. Software*, in press.

Stockle, C. O., Donatelli, M., and Nelson, R. (2003). CropSyst, a cropping systems simulation model, *European J. Agron.*, **18**, 280–307.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2009). *A Summary of the CMIP5 Experiment Design*. Available at: http://cmip-pcmdi.llnl.gov/cmip5/docs/Taylor_CMIP5_design.pdf. Accessed on 21 December 2013.

White, J. W., Hoogenboom, G., Kimball, B. A., and Wall, G. W. (2011). Methodologies for simulating impacts of climate change on crop production, *Field Crops Research*, **124**, 357–368.

Zhang, Y., Rossow, W. B., and Stackhouse, P. W. Jr. (2007). Comparison of different global information sources used in surface radiative flux calculation: Radiative properties of the surface, *J. Geophys. Res.*, **112**, D01102.

Section IV

Building AgMIP Science

This page intentionally left blank

Chapter 9

Uncertainty in Agricultural Impact Assessment

Daniel Wallach[1], Linda O. Mearns[2], Michael Rivington[3],
John M. Antle[4], and Alexander C. Ruane[5]

[1]*L'Institut national de la recherche agronomique, Castanet Tolosan, France*

[2]*National Center for Atmospheric Research, Boulder, CO, USA*

[3]*The James Hutton Institute, Aberdeen, Scotland*

[4]*Oregon State Univeristy, Corvallis, OR, USA*

[5]*NASA Goddard Institute for Space Studies, New York, NY, USA*

Introduction

This chapter considers the issues concerning uncertainty associated with modeling and its use within agricultural impact assessments. Information about uncertainty is important for those who develop assessment methods, since that information indicates the need for, and the possibility of, improvement of the methods and databases. Such information also allows one to compare alternative methods. Information about the sources of uncertainties is an aid in prioritizing further work on the impact assessment method. Uncertainty information is also necessary for those who apply assessment methods, e.g., for projecting climate change impacts on agricultural production and for stakeholders who want to use the results as part of a decision-making process (e.g., for adaptation planning). For them, uncertainty information indicates the degree of confidence they can place in the simulated results. Quantification of uncertainty also provides stakeholders with an important guideline for making decisions that are robust across the known uncertainties (Lempert *et al*., 2004). Thus, uncertainty information is important for any decision based on impact assessment. Ultimately, we are interested in knowledge about uncertainty so that information

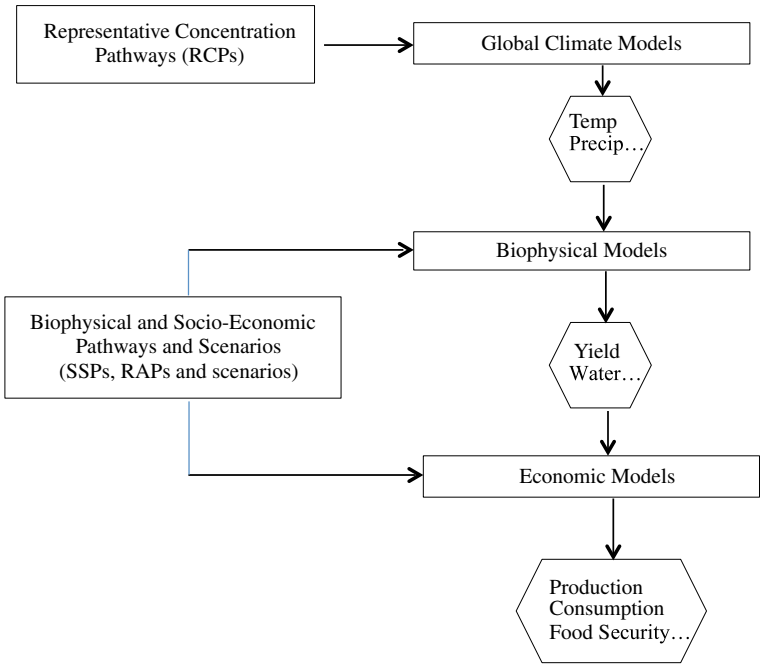


Fig. 1. General modeling structure of agricultural and food-system impact assessments.

can be used to achieve positive outcomes from agricultural modeling and impact assessment.

The systems involved in assessing the impact of climate change on crop production and society are complex, and the prediction uncertainties necessarily quite large (Jones, 2000). The issues at stake, whether they are the estimation of future global food production, or decisions on investments for adapting agriculture to global warming, are so important that they necessitate thorough evaluation of the uncertainties involved (Asseng *et al.*, 2013; Challinor *et al.*, 2014; Rosenzweig *et al.*, 2013a; Rötter, 2014; Rötter *et al.*, 2011). The original mandate of the IPCC, in 1988, included "(a) Identification of uncertainties and gaps in our present knowledge with regard to climate changes and its potential impacts" (IPCC, 2007a).

Figure 1 presents a schematic of the cascade of models involved in impact assessment. A distinction is made between scenarios of possible future development (on the left) and models (on the right). In this chapter, we concentrate on the uncertainties associated with the models in each domain (climate, crop, economics), and in cascades of models. Note that global climate models (GCMs) may require downscaling before feeding into the biophysical models, and biophysical models may require upscaling before feeding into the economic models. Downscaling and upscaling bring additional uncertainty.

We first define uncertainty and other related terms, and the role of AgMIP. We then describe methods for evaluating uncertainty that are common across models. While much of the methodology is common across disciplines, the applications are field-specific. Thus, we subsequently consider separately the sources and evaluation of uncertainty in climate, crop, and economic models. (For further complementary information on each of these fields, see the corresponding chapters in this volume). We then discuss how to report and communicate uncertainties. A major objective of uncertainty analysis is to identify the major causes of uncertainty. A brief discussion of methods for doing this is then presented. The final section identifies challenges still outstanding on the road to obtaining systematically reliable quantification of uncertainty in impacts assessment.

What is uncertainty?

Uncertainty generally refers to a state of incomplete knowledge that results from a lack of information or from disagreement about what is known or even knowable. In the context of determining future effects of climate change on crops and agriculture, uncertainty measures the extent to which we are able to predict or project exactly the unknown outcomes. More specifically, for our purposes, uncertainty measures the extent to which unknown outcomes simulated by models may differ from true outcomes. The quantification of uncertainty is most often represented by a probability distribution, which gives the probability of different distances between the true outcome and the simulated value.

It is useful to distinguish two situations: A case where one can conduct, or at least envision, multiple repetitions of the same experiment, and another case in which no repetitions are possible. Predictions or estimations with crop models are generally in the first category. For example, an experiment might measure yield in a field of wheat drawn from some population of fields and weather sequences. One can envision yield measurements in multiple fields drawn from the same population of fields, and corresponding model simulations. The uncertainty in this case would be represented by the distribution, for the entire population, of true minus simulated yields. Another example is next-day predictions or forecasts of weather at a particular location. Once again, these are predictions that could be repeated multiple times (e.g., over a sequence of days). The uncertainty here would be represented by the distribution of true minus forecasted weather, over all possible prediction days. In both these cases the exact uncertainty (the distribution of true minus simulated values over the entire population of interest) is unknown. It can, however, be estimated, as explained in the next section. We speak of predictions in the sense that the simulations concern unknown quantities, whether in the past (diagnostic use of models) or the future (prognostic use of models).

When considering climate change on the other hand, there is no possibility of multiple realizations. There will only be a single realization of climate at, say, 2050. Uncertainty in this case is still quantified by using a probability distribution, but now that distribution represents how uncertain we are about a future outcome, and not how often an outcome will occur. Once again, we can estimate this uncertainty by using the methods presented in the next section.

Some vocabulary

Uncertainty is an issue that cuts across research disciplines, and has associated terminology that may differ. It is thus important to establish a vocabulary that facilitates communication across disciplines and between researchers. Existing definitions in the literature of key vocabulary and terms may be interchangeable (i.e., Refsgaard *et al.*, 2007), but risk misapplication and misinterpretation (i.e., Norton *et al.*, 2006; Walker *et al.*, 2003). A fundamental starting point is to define the basic terms used on which subsequent terminology can be built, based on dialogue and consensus between disciplines:

- *Source* (alternatives terms used include "location" or "type"): Where the uncertainty comes from, i.e., where and what causes errors to exist (internal or external to the impact assessment) and how they manifest themselves within a model, an ensemble of models (e.g., scenario, ensemble, parameters, input data, model equations) and overall integrated research process.
- *Level* (alternative terms used include "degree" or "scale"): The *amount* of uncertainty and its association with the size of an error. The *level* can be expressed quantitatively as a range (e.g., standard deviation, probability distribution) or qualitatively (e.g., vocabulary such as "high", "medium", or "low").

Above we distinguished between emissions or concentration scenarios of greenhouse gases (GHGs) and models of climate and crops. A scenario is a "plausible description of how the system and/or its driving forces may develop in the future" (Walker *et al.*, 2003). There is no attempt to assign probabilities to these alternative futures, because they depend on decisions in human society that are not predictable. Such decisions may include degree of investment in alternative energy in the future, or whether a binding international agreement on mitigation targets is ever reached. In general, there is a number of distinct emissions or concentration scenarios, and projections of future climate are made separately for each emissions or concentration scenario. The number of emissions scenarios can be quite large, but in the context of the IPCC, usually a smaller subset is used for use by the climate modeling community. Similarly, one would only consider a small number of biophysical and

socio-economic pathways and scenarios. Impact assessment would then be done separately for each scenario.

This is related to the distinction between predictions and projections (MacCracken, 2001; IPCC, 2013). The distinction is especially important for climate models. For the short-term (i.e., weather) and under certain circumstances of model initialization, one talks of predictions or forecasts. Forecasts also tend to be verifiable over short time-scales (e.g., days, seasons). For the longer-term future, climate models make projections, which are statements of what might happen in the future for given emission or concentration scenarios (IPCC, 2013). A projection is a simulated response of the climate system to a scenario of future emissions or concentrations (of GHGs and aerosols; IPCC, 2013). For crop models, "predictions" mean the testable response of a crop to given inputs. When climate projections are used as inputs to the crop model then, for the sake of coherency, the term "crop model projections" is used. For economic models, projections, refer to what might happen in the future.

The two terms, "error" and "uncertainty", are often used interchangeably. What exactly is the relationship between them? "Error" measures the distance between measurements and values simulated with a model. As we use it in this chapter, "uncertainty" measures the distance between true (but as yet unobserved) values in the future and simulations of the future. Under certain circumstances, the distribution of errors in the past may be used to estimate uncertainty for future simulations. However, this involves an implicit assumption about the relationship of past performance to the future, which is often a questionable one and needs investigation.

A third term, "risk", is often the entry point for many stakeholders and decision-makers, as it translates uncertainty into actionable information. Risk is a measure of the probability of some event times the consequences of the event. It thus combines uncertainty with the consequences of the various outcomes. According to Parry *et al.* (IPCC, 2007b), "the concept of risk, which combines the magnitude of the impact with the probability of its occurrence, captures uncertainty in the underlying processes of climate change, exposure, sensitivity, and adaptation".

The role of AgMIP in uncertainty estimation

The Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013a) is a multi-faceted project that focuses on model intercomparison, model improvement, and model application in climate change impact assessment. Of particular interest for this chapter are its contributions to better understanding, characterization, and quantification of uncertainty and how it is communicated.

In the context of climate models, it has become common to evaluate uncertainty by using multi-model ensembles; the variability across models is taken to represent the uncertainty in the simulated results (as described in more detail below). For crop

and economic models, however, this approach is much more recent (Asseng *et al.*, 2013; Nelson *et al.*, 2014a; Palosuo *et al.*, 2011; Rosenzweig *et al.*, 2013b; Rötter *et al.*, 2012). A major contribution of AgMIP (and of related regional networks like the European Joint Programming Initiative for Agriculture, Food Security and Climate Change (JPI FACCE) and its modeling project MACSUR) has been to promote studies using ensembles of crop or livestock models.

A multi-model ensemble approach offers the further benefit of allowing the evaluation of uncertainty in cascades of models, in particular of climate models that feed weather information into crop models and of crop models that pass yields into economic models.

Methods for Quantifying Uncertainty

The methods for estimating uncertainty are largely shared among climate, crop, and economic models.

In very general terms, any model can be written as

$$Y = f(X; \theta) + \varepsilon \tag{1}$$

where Y is the true value of the output of interest, f is the model function, X is the vector of explanatory variables, θ is the vector of parameters, and ε is model error (which may be non-linear). For the models of interest here, f can be very complex (tens or hundreds of equations) and X and θ can have high dimensions (with hundreds or thousands of elements).

We are interested in obtaining the distribution of $\varepsilon = Y - f(X; \theta)$ for some range of situations of interest. This distribution represents the uncertainty when we refer to situations involving the future. We have basically three different ways of estimating that uncertainty, as detailed below.

Estimate uncertainty of predictions/projections based on the error in hindcasts

Using hindcasts, the basic assumption is that errors in future years will have the same distribution as errors from past years. If we have hindcasts for a model, we can use the probability distribution function (PDF) of the errors in those hindcasts as our estimate of the PDF for errors (or uncertainty) in the future. Or more simply, we can use the average square error of past errors as an estimate of average square error for future predictions or projections.

This assumption will be justified if both the past and future conditions are random samples from the same underlying population. Specifically, we assume that we have a sample of measured (without error) and simulated values for a random sample of

situations from the population of interest. The errors for the sample are

$$\varepsilon_i = Y_i - f(X_i; \theta) \tag{2}$$

The distribution of these errors is then an estimate of the distribution of ε for the full population, i.e., of the uncertainty in the predictions or projections.

Note that this approach estimates prediction uncertainty for the model which has some specific parameter values. Whatever uncertainty there may have been in choosing parameter values, some specific values have been chosen and it is the prediction uncertainty associated with the model with those values that is evaluated.

The advantage of this approach is that it automatically accounts for all sources of error. We do not need to specify what is causing the errors in prediction or projection. The errors can result from the model equations, the parameter values, the incompleteness of the model, the model input values, the way in which the model predictions are upscaled or downscaled to correspond to observed data or other sources. Any or all of those may contribute to the difference between observed and simulated values; we do not need to know specifically what the causes of error are.

The assumption that past and future errors have the same distribution may be reasonable for near-term (say ten years into the future) climate predictions. It is also reasonable in certain cases for crop models, though it should be recognized that cultivars and management practices evolve over time.

The major problem with this approach is that the validity of the basic assumption is questionable when assessing projections of more distant, future climates. The future world may be quite different from the present with respect to some of the major determinants of climate (in particular CO_2 and other GHG concentrations). The main way in which these conditions are tested is by driving climate models with changes in the forcing, e.g., future changes in the concentrations of GHGs and aerosols. However, we have no direct means of testing (against data) whether the climate models are responding correctly to changed forcings.

For crop models, it is also often questionable whether past errors are representative of errors under a future climate. For example, hindcasts may not test the model for extreme temperatures, and do not test for increased CO_2 concentrations. However, it is possible to carry out specific experiments to test the models for possible future temperatures and CO_2 concentrations. The problem is that the necessary experiments are difficult and costly, and so there are relatively few of them. Thus we only have appropriate hindcast errors for a limited number of situations (crops, soils, management, etc.). This means that we can only estimate a mean square error of prediction, not a full PDF, and only for certain types of situation (crops, soils, management).

Many of the economic models used in AgMIP activities are equilibrium models, meaning that they simulate the settled economic state given shifts in key drivers

(e.g., population, income, food demand, trade policies) and a system's ability to respond (for example, *via* elasticity of land-use and investment opportunities). These alternative states are similar to future climate conditions in that they are not directly testable. Equilibrium models also do not directly account for the uncertain transition from the current to the future equilibrium states.

If past data have been used to estimate model parameters (often referred to as model calibration or model tuning), then hindcast errors for that same data are no longer representative of future errors, even if the past sample is representative of future situations in which the model will be used. The goodness-of-fit of a calibrated model in general underestimates the error in future predictions (Efron, 1986). One possible approach, in order to get a more realistic estimate of uncertainty, is to do some kind of data-splitting to separate the data for calibration and the data used to evaluate error (Efron, 1983).

There are a number of practical problems that can arise with the use of hindcasts. One of these is measurement error. In general, the observed value is itself only an estimate of the true value. This will in general inflate observed error, compared to the error in simulating true response values. Another problem is sampling. The sample of situations for which we have hindcasts may not be representative of the full population of interest, in which case the hindcast errors may be unrepresentative of uncertainty for that population. Sampling the population of interest is often particularly problematic for crop models (Wallach *et al.*, 2014).

Estimate the uncertainty for individual models by using an error-propagation approach

In considering error-propagation, the general procedure is to posit a probability distribution for the uncertain factors (usually model parameters or input variables), run the model multiple times with different values drawn from that distribution, and then take the resulting distribution of outcomes as a representation of the uncertainty resulting from the uncertainty in those factors.

Consider the effect of parameter uncertainty on crop model predictions. Equation (2) can be written as:

$$\varepsilon_i = [Y_i - f(X_i; \theta^{ref})] + [f(X_i; \theta^{ref}) - f(X_i; \theta)] \tag{3}$$

where θ^{ref} is some reference value of the parameters and θ is the value used in the model. In the approach here, the objective is to estimate the distribution of the second term on the right. However, as Equation (3) shows, this method should just be considered as a way of estimating only one part of the overall error.

One first assumes a joint distribution function for $\theta - \theta^{ref}$. To simplify, one often assumes independence, so that the joint distribution function is the product of

the individual distribution functions. The distribution for each individual parameter often comes from the literature, and represents the range of values for the parameter that has been reported. Then one does a Monte Carlo study, by sampling from the distribution of parameter values and evaluating the model outputs. The resulting distribution of $f(X_i; \theta^{ref}) - f(X_i; \theta)$ is an estimate of the uncertainty in the outputs due to uncertainty in the parameters. Note that the uncertainty here is somewhat different than that estimated using hindcasts. There uncertainty referred to the model with fixed values for all the parameters. Here the uncertainty is on the average over models with θ drawn at random from the distribution of $\theta - \theta^{ref}$.

Often one only estimates the uncertainty in a subset of the parameters. Many or even most of the parameters are fixed. In this case, one is evaluating the uncertainty of the model due to uncertainty in the chosen subset of the parameters, for the model that has fixed values of the remaining parameters.

This approach has been used to estimate uncertainty in climate model simulations due to parameter uncertainty. A model is run with multiple values for each of the uncertain parameters, and the resulting distribution in the output is the uncertainty due to uncertainty in the parameter values. However, runs with values of the parameters that produce unrealistic climate results are eliminated from the resulting ensemble of runs. The multiple models created in this way from a single starting model are referred to as parameter permutation experiments (PPEs) or ensembles in the climate modeling community, not to be confused with multi-model ensembles (MMEs; e.g., Parker, 2013).

As noted, the distribution for each parameter often comes from the literature. A different approach is to estimate the parameter values from data by using a statistical procedure. In that case the statistical procedure in general provides information about parameter uncertainty. If the calibration uses a frequentist approach, then the resulting parameter uncertainty represents the uncertainty related to the sample; different samples would lead to different estimated values. If a Bayesian approach is used, then the uncertainty represents our level of ignorance given our prior information and the specific sample we have. In both cases, the statistical procedure in general also provides an estimate of the variance of residual error, which is related to the first term on the right in Equation (3).

Uncertainty due to uncertainty in input variables (which include initial conditions) can also be estimated by using an error-propagation approach. In several studies, a climate model has been run multiple times with different starting days (and therefore different initial conditions), in order to obtain the distribution (uncertainty) in the outputs. There have also been studies of the effect of input uncertainty on crop models (i.e., Aggarwal, 1995; Mearns *et al.*, 1999; Rivington, 2006; Roux *et al.*, 2014). Ruane *et al.* (2013) investigated various initialization times to gauge uncertainties stemming from crop model spin-up. A major input uncertainty of interest

for crop models that are used in impact assessment is uncertainty in climate. One can use multiple climate models (a multi-model ensemble, a PPE, or a model with multiple initial conditions) to represent the uncertainty in climate, and then run a crop model for each of those inputs.

Error-propagation can also be used to evaluate uncertainty due to sources other than model parameters or input variables. For example, one can run the same GCM model using different downscaling approaches in order to evaluate the uncertainty caused by the downscaling method (Mearns *et al.*, 2013b).

In crop modeling, one can run the same crop model with different methods of upscaling (from field to region) in order to evaluate the uncertainty due to the upscaling procedure (see Part 1, Chapter 10 in this volume). Consider, for example, upscaling a crop model from field to region, to predict average regional yield. In this case, the model error can be written

$$\varepsilon_i = \left[Y_i - \bar{f}(X_i;\theta)\right] + \left[\bar{f}(X_i;\theta) - f^{est}(X_i;\theta)\right] \tag{4}$$

where $\bar{f}(X_i;\theta)$ is simulated yield averaged over all fields in the region and $f^{est}(X_i;\theta)$ is an estimate of average regional yield. Again, the approach here attempts to estimate the distribution of the second term. If, for example, $f^{est}(X_i;\theta)$ is the average of simulated values over a sample of fields, then the PDF of the second term on the right is the distribution of sample averages around the average over all fields in the region.

In principle, an error-propagation approach could be used to quantify the uncertainty due to uncertainty in the model equations. To do so one would specify the possible alternative equations, and then create and run models for each of those possibilities. In practice, however, this is difficult to do, starting from a specific model. That is the motivation for multi-model ensembles in which the models come from multiple research teams (see below).

An advantage of this approach is that one can study how specific types of uncertainty propagate through the model to create uncertainty in outcomes. For example, one can study specifically the consequences of uncertainty in the parameters, or just in certain parameters. Furthermore, as Equation (3) shows, the uncertainty that one calculates is specific to some situation (some specific value of X), so that one is obtaining very detailed uncertainty information.

A disadvantage of this approach is that it only considers part of overall uncertainty, and there is, in general, no guarantee that this is the major contribution to uncertainty. A second difficulty is obtaining realistic estimates of the uncertainties in the uncertain factors. Crop models, for instance, often have several tens of or a few hundred parameters, and many of these parameters only have meaning within

the context of the crop model. It is unclear then how to quantify the uncertainty in those parameters.

Estimate uncertainty based on multi-model ensembles

In both climate and crop modeling, multiple research groups around the world have developed different models that can be used for predicting the same outcomes. Rather than selecting a single model and accepting its results, estimates based on multi-model ensembles use the variability between the different models as an estimate of uncertainty in the predictions or projections. For example, one could obtain an 80% confidence interval by removing the largest and smallest 10% of simulated values.

Here we write Equation (2) as:

$$\varepsilon_i = \left[Y_i - f^{ref}(X_i; \theta)\right] + \left[f^{ref}(X_i; \theta) - f(X_i; \theta)\right] \tag{5}$$

where $f^{ref}(X_i; \theta)$ is some reference model. The objective is to estimate the distribution of the second term on the right. In many cases $f^{ref}(X_i; \theta)$ is taken as the mean of the predictions of the models in the ensemble. Then the distribution of interest is that of $f^{mean}(X_i; \theta) - f(X_i; \theta)$, i.e., of the multiple models around their average.

One advantage of this method is that it accounts for uncertainties in model structure and equations. It would be very difficult for a single modeling group to explore the range of possible models. That would require putting aside and forgetting the current model and starting from scratch to build a new plausible model, and redoing that multiple times. It is essentially that result that is obtained by using models developed by different modeling groups.

This method of using multiple models run by different modeling groups also takes into account, at least to some extent, uncertainties in model parameters, since each modeling group may use different values for those parameters that are in common among different models. Another advantage of this approach is that one can evaluate the uncertainty as a function of the situation (value of X).

A final advantage of this approach is that it is well adapted to studying the uncertainties in cascades of models. Suppose, for example, that we want the uncertainty in predicting wheat yield under future climate, which takes into account both the uncertainty in future climate and the uncertainty in predicting wheat yield when climate is known. Given ensembles of both climate and crop models, we simply run all combinations and take the final spread of results as our measure of uncertainty. One can also combine a multi-model climate ensemble with multiple versions of a crop model, in which each version differs in the values of the parameters (Tao *et al.* 2009; Tao and Zhang, 2010).

A major shortcoming of the multi-model approach is that there could well be cases in which all the models agree quite closely but all the models are wrong. Then true uncertainty is large, but uncertainty estimated from the multi-model ensemble is small. In Equation (5), with $f^{ref}(X_i;\theta) = f^{mean}$, this would correspond to the case in which the first term on the right, which is ignored, is large, and the second term on the right, which is taken to represent uncertainty, is small. In any case, even if the first term on the right doesn't dominate, it still represents a contribution to uncertainty that is ignored in this approach.

There are practical difficulties in quantifying uncertainty by using multi-model ensembles. Each study requires the collaboration of multiple modeling groups; the definition of a shared protocol for performing the simulations and making the output available to the larger scientific community, so that different methods of combining and analyzing all the information can be developed. The strength of AgMIP is that it has provided the framework where ensemble studies (involving both crop and climate model results) can be routinely produced.

To explore more thoroughly the range of factors of which the uncertainties lead to uncertainties in model predictions, one can combine this approach with the error-propagation approach of the previous section. For example, one can run not only multiple models, but also for each model multiple parameter values and/or multiple input values (these are referred to as "super-ensembles"; Nelson *et al.*, 2014a; Rosenzweig *et al.*, 2013b). In this way, one can explore more thoroughly the range of factors of which the uncertainties lead to uncertainties in model predictions.

There is a number of open questions concerning the use of multi-model ensembles to quantify uncertainty. Many revolve around the question of how best to ensure that the ensemble is really sampling the space of plausible models. There are also questions as to whether weighting the models of the ensemble other than equally might lead to less uncertainty.

A word of warning — the unknowns

In climate impact assessment for agriculture, we are trying to predict the effect of climate on crop production, and the economic consequences of that effect in a future world. Our uncertainty estimates quantify what we know about the extent of our ignorance. We cannot quantify the ignorance we don't know, but we should certainly be aware of the possibility that our uncertainty estimates under-represent true uncertainty (Spiegelhalter and Riesch, 2011).

This is in addition to known limitations to the models. For example, we know that pests and diseases reduce crop yields, and that their incidence will change under climate change, but almost all crop models ignore biotic yield-reduction factors. This again will increase uncertainty, in ways that are hard to quantify.

Uncertainty in Climate Model Simulations

Current climate as input for crop models

There are various uncertainties in climate data, due to sparseness and various inaccuracies in observed climate datasets. Observed datasets do not always agree with each other due to different raw data sources, different means of handling missing data, differing spatial resolutions of the data, and different means of aggregation and interpolation (e.g., Mearns *et al*., 2012).

As input for crop models, there is also the issue of generating some of the data, for example, through use of weather generators. An important advantage of using weather generators is that many iterations of weather sequences can be generated (e.g., hundreds or thousands) and thus a large sample of extreme events can be created and used for input to the crop models. However, there is evidence that weather generators are not completely reliable in reproducing all of the relevant aspects of weather patterns (Kim *et al.*, 2012; Wilks, 2012).

Future climate

The uncertainty in short-term weather forecasts can be precisely determined by quantifying/assessing how accurate the forecast was on one day, based on what actually happened on that day. However, we cannot reasonably use past error to evaluate the uncertainty in projections of long-term climate change (e.g., the 2020s to the 2090s). The problem is that the future climate patterns will not simply be like the past. The increase in GHGs and aerosols is changing the forcing on the climate system, and validation for past climates in no guarantee of "accuracy" for future climates.

There are primarily three kinds of uncertainty that are relevant to projecting future climate change. These are: (1) the trajectory of future emissions and/or concentrations of GHGs and aerosols; (2) uncertainties regarding how the climate system will respond to these concentrations (explored through the use of climate models); and (3) the natural internal variability of the climate system (also explored using climate models). We discuss each of these sources below.

Emissions and concentration pathways

Perhaps the most difficult uncertainty regarding possible future climate is the trajectory of emissions of GHGs and aerosols and their concentrations that will determine the transient future forcing to which the climate system will be subjected. To determine this future forcing, one must explore how we believe the world will develop regarding population, technological development, socio-economic conditions, political structures, ecosystem function responses, and land use. This is truly

a daunting task. This uncertainty becomes more and more important as we move further away from present conditions.

There have been two major organized efforts to investigate possible futures in this regard:

- The Special Report on Emission Scenarios (SRES) scenarios (Nakocenovic and Swart, 2000; including the A2, B1, and A1FI scenarios) that have been used to drive global climate models for over a decade
- A new suite of concentration pathways (representative concentration pathways; RCPs) that have been used only in the past few years to drive the newest versions of climate models used in the IPCC Fifth Assessment (AR5) WG1 Report (IPCC, 2013; Moss *et al.*, 2010).

Since the majority of climate simulations used in AgMIP are driven by the RCPs, we only discuss those in detail below. There were numerous motivations for developing this new approach and set of scenarios. This included the need for scenarios that embraced mitigation policies, that extended beyond 2100, and that would speed up the entire assessment process. The RCPs are defined as the radiative forcing that would be obtained at the end of this century expressed in units of watts per meter^2 (W m^{-2}). There are four primary RCPs: 2.6, 4.5, 6.0, and 8.5 (W m^{-2}). These RCPs represent the literature with regard to the range of with scenarios of radiative forcing. Figure 2 shows the radiative forcing of these same scenarios as well as that of the older SRES scenarios for comparison. The RCPs were used to drive global climate models as part of the CMIP5 effort (Taylor *et al.*, 2012; see section below on ensemble climate uncertainties).

Further developments of this system entail the development of SSPs and extended SSPs. These refer to new descriptions of future socio-economic reference conditions that underlie challenges to mitigation and adaptation. The socio-economic information, the RCPs, and the associated climate change projections will eventually be integrated to develop scenarios for use by the climate science community (Van Vuuren *et al.*, 2013). In general, these emission and concentration pathways are not described in a probabilistic framework, but are viewed as individual scenarios of the future with more or less equal plausibility. A special issue of the journal *Climatic Change* has been prepared (Ebi *et al.*, 2014) that documents the many aspects of the new framework.

Uncertainty in the climate response to forcing (*climate system response*)

While most global and regional climate models are carefully constructed and evaluated, they do not necessarily respond in the same way to a given future forcing scenario (e.g., an RCP). These differences are due to uncertainties about how the

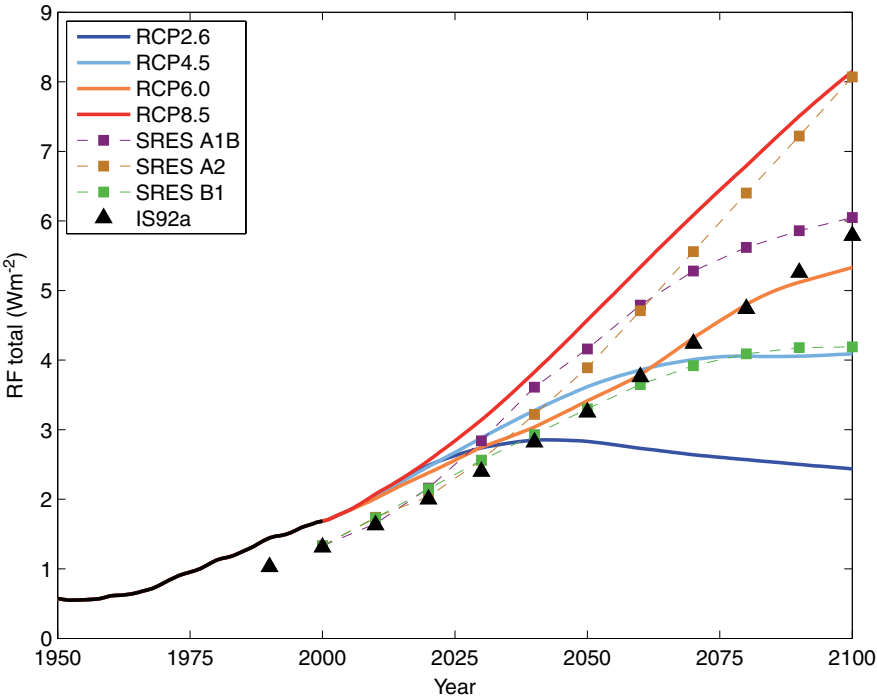


Fig. 2. Total anthropogenic radiative forcing (RF) relative to the pre-industrial period for the RCPs, some SRES scenarios, and an earlier scenario used in the 1992 IPCC report (from IPCC, 2013). This is Figure 1.15 from the IPCC (2013), reproduced with permission.

climate system works, differences in the way various subsystems are modeled (e.g., land-surface processes), and differences in how unresolved processes are parameterized (e.g., convection).

It is common to use multi-model ensembles (MMEs) to quantify the uncertainty represented by the different models. Uncertainty is based on the spread in simulations with different climate models that are subjected to the same future radiative forcing or atmospheric composition. These MMEs play a central role in the analyses that contribute to the various IPCC assessments (e.g., sets of simulations from CMIP3 and CMIP5 for the Fifth Assessment Report (AR5), IPCC, 2013).

In AR5 (IPCC, 2013), a large ensemble of simulations was produced primarily by using the key RCPs, particularly RCP 4.5 and 8.5. At least 25 different climate models were used in the development of the set of climate simulations, commonly referred to as CMIP5 (Taylor *et al.*, 2012). Global temperature results of these experiments are shown in Fig. 3.

An important issue in determining uncertainties in the context of multi-model ensembles is whether one follows the "one model, one vote" principle or weights the

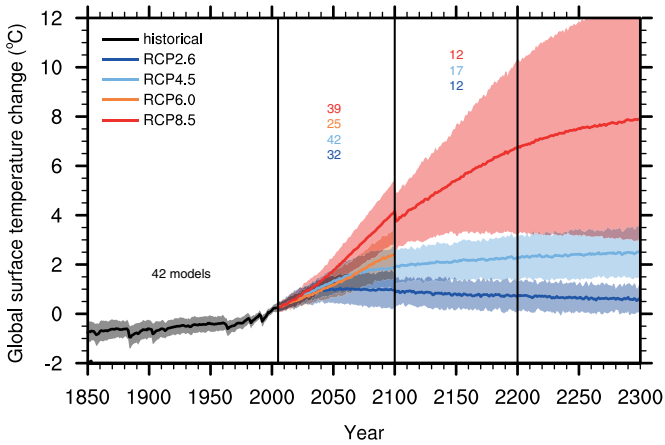


Fig. 3. Time-series of global annual mean air temperature anomalies (relative to 1986–2005) from CMIP5 concentration-driven experiments for the four indicated RCPs. The different color-coded numbers indicate the number of models used to produce each set of simulations for each RCP. The difference in the number of models after 2100 explains the discontinuity at that point in time. This is Figure 12.5 in IPCC (2013), reproduced with permission.

models differently based on some evaluation of model quality (Knutti, 2010). While there have been numerous explorations of this issue (e.g., Giorgi and Mearns, 2002, 2003; Pierce *et al.*, 2009; Santer *et al.*, 2009; Tebaldi *et al.*, 2005; Tebaldi and Knutti, 2007), there remain no definitive conclusions regarding proper weighting of climate models for quantifying the uncertainty of future projections. Hence, in the most recent IPCC report (Collins *et al.*, 2013; IPCC, 2013), equal weighting of MMEs is generally followed. For particular purposes, a model selection may be necessary due to resource limitations. For example, Ruane *et al.* (Part 1, Chapter 3 in this volume), describe how five GCMs were selected to represent the uncertainty of the climate system response for use in crop and economics modeling. Criteria included model reputation (modeling centers that have a long history of CMIP participation), quality (e.g., in representing monsoon dynamics), and spatial resolution. This subset's mean temperature and rainfall were compared against a larger 20-GCM ensemble to provide context for interpretation of the downstream crop and economic model results.

An additional element in the uncertainty of climate system response is added when global climate models are further downscaled to provide higher-resolution climate simulations (e.g., 25 or 10 km spatial scales). This is generally accomplished through the application of dynamical regional climate models or statistical models (Mearns *et al.*, 2003; Wilby *et al.*, 2004). These techniques use the large-scale forcing from the global models, but then provide unique solutions on the finer scale. Different regional models, which use the same global model boundary conditions, can produce different climate changes, and these changes can also be different

from those obtained with statistical downscaling (Mearns *et al.*, 2013a, 2013b). Of particular relevance to AgMIP is the Coordinated Regional Downscaling Experiment (CORDEX; Giorgi *et al.*, 2009), which has provided a framework for dynamical downscaling over most land areas driven by the CMIP5 global model simulations and multiple regional climate models. Once again, MMEs are used to estimate the uncertainty represented by different regional climate change projections. However, one limitation of CORDEX is that neither the same global models nor regional models are used in all regions.

One can also look specifically at the uncertainty in projections due to uncertainty in parameter values. Here the uncertainty is estimated for each model. Multiple models developed from a single climate model of which the parameters are varied in systematic ways are referred to variously as parameter permutation experiments or perturbed physics ensembles (PPEs) (e.g., Murphy *et al.*, 2007). Each "new" model is subjected to the same external forcing, and the spread between simulated values is taken to represent the uncertainty due to parameter uncertainty. Most often parameters in the atmospheric model component of the AOGCM (Atmosphere-Ocean General Circulation Model) are perturbed but more recently parameters in the ocean model and land-surface components have been subject to permutation experiments.

Finally, researchers have also produced so-called super-ensembles wherein PPEs and MMEs are combined and the results rendered probabilistically (e.g., Sexton *et al.*, 2011; Sexton and Murphy, 2012). However, it is important to note that neither MMEs nor PPEs represent all possible choices of climate model formulation. Also, MMEs and PPEs consider different modes of uncertainty, and one cannot be viewed as an analog for the other. PPEs have now been generated by using the newer earth system models (ESMs), to produce the so-called ES-PPEs. Murphy *et al.* (2014) compared CMIP3 and CMIP5 AOGCM MMEs with ES-PPEs for various regions. The ES-PPEs tend to span a larger range of uncertainty, but the range does not overlap very much with that of the MMEs.

Internal climate variability

Long-term projections of climate change are subject to uncertainty resulting from the internal variability of the climate system. The relative role of this type of uncertainty compared to the other sources of uncertainty (climate model response uncertainty and forcing uncertainty), is a function of the future time horizon being considered and the spatial scale of analysis (Hawkins and Sutton, 2009, 2010). Internal variability is usually explored by running sets of climate model simulations (ensembles) by using different initial conditions for each simulation. Recent research has explored large numbers of ensemble members (e.g., Deser *et al.*, 2010) and has thus come up with improved measures of internal variability. In this case 40 different members

were produced, which represent how much the climate can vary based on random internal variations. The variations across ensemble members can be considerable on various spatial scales, and there is evidence that this kind of uncertainty may not be reducible (Deser *et al.*, 2012).

Translation of climate model output to input for crop models

In recent years, more attention has been paid to how the raw output from the climate simulations is translated into climate-input datasets for crop models (see Fig. 1). This translation is another source of uncertainty, since the different methods of translation use different aspects of the raw model output.

For years, a very simple method, called the delta method, was used for this purpose (Mearns *et al.*, 2003). Essentially climate observations (e.g., temperature, precipitation, relative humidity) were used for inputs to determine the effect of current climate on crops, and for the future, the change in climate (future=current, difference for temperature, and ratio for precipitation) was imposed on the observations to produce the needed input. This method changes the means of temperature, but not the variance. When applied to precipitation, it changes both the mean and variance of precipitation, but does not affect the number of rainy days. Means of altering the variability of temperature and the frequency of dry and wet days have been developed by using weather generators (see Wilks (2012) for a review, and Part 1, Chapter 3 in this volume).

In recent years other (perhaps more complete) methods have been used to "correct" for the biases in the climate simulation data. One common method is the bias-correction spatial disaggregation approach (BCSD; Maurer *et al.*, 2002, 2007) that both corrects for bias throughout the entire distribution of the raw data by using quantile mapping, and spatially disaggregates the data to a resolution useful for, for example, hydrologic studies. Simple methods for site-specific bias correction of daily weather variable data for regional climate models (RCMs) have also been developed (i.e., Rivington *et al.*, 2008) that may facilitate estimation of bias-corrected data for sites with adequate observations of crop growth and weather.

Such corrected and spatially disaggregated data have been produced for the CMIP5 simulations (Thrasher *et al.*, 2013). The salient point regarding uncertainty is that the method of translation of the raw data adds an additional uncertainty to the current and future climate that is used as input to the crop models. For any application, it is important to recognize that the selection of variables included in the scenario generation process may affect the results and their uncertainty.

Uncertainty in Crop Model Simulations

Multiple crop models exist for the major world food crops, and there have been numerous studies to evaluate these models. Such evaluations have for the most

part concerned individual models, and estimations for current conditions rather than for future climate. Only recently have there been studies that specifically consider the uncertainty in crop model projections for future climate, in particular for increased temperatures and CO_2 levels (e.g., Asseng *et al.*, 2013; Ruane *et al.*, 2013, 2014a).

There have been numerous studies in which error for individual models has been evaluated by using historic data. Examples, chosen from among many, of evaluation of model error can be found in Abedinpoura *et al.* (2012), Mkhabela and Bullock (2012; prediction of wheat grain yield by AquaCrop), Soler *et al.* (2007), and Ben Nouna *et al.* (2000; prediction of maize yield by CERES-maize).

Often, evaluation is based on a small set of data representing a limited range of environments. Since there are few data, in general the studies do not try to estimate the PDF, but rather simply calculate a summary statistic of error. The most common is root-mean-square error (RMSE), defined as $RMSE = (1/n)\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$, where n is the number of data points, Y_i the observed data, and $\hat{Y}_i$ the simulated values. One also finds mean absolute error (MAE) and Nash–Sutcliffe efficiency (Krause, *et al.*, 2005), as well as several other measures. As explained earlier, the estimates of error could be taken as estimates of uncertainty in predictions, if it is assumed that the predictions concern the same population as the past errors.

It should be emphasized that with very few data, model calibration and also model error are based on only a very small subset of the conditions of interest. Then the estimated error will depend on the specific sample used; if a different sample were used, very different results might be obtained. General discussions of issues involved in crop model evaluation can be found in Bellocchi *et al.* (2010) and Wallach *et al.* (2014).

There have also been a few studies specifically of the capability of crop models to predict the effect of elevated CO_2 on crop growth. In Biernath *et al.* (2011), four different models were first calibrated using a control treatment, and then tested against the data for spring wheat grown in enriched CO_2 environments.

There have been multiple studies in which the effect of parameter uncertainty on crop model uncertainty has been evaluated, by using error-propagation with parameter values drawn from the distribution of possible values. A major difficulty here is obtaining reasonable ranges for the parameter values. For some parameters there are ranges of values in the literature, based on studies of individual processes, but, in general, models also include other parameters that have not been studied. For example, Richter *et al.* (2010), who used a model developed in the STAMINA project to simulate durum wheat, use "calibrated values or data derived from literature" where possible, and otherwise "a default standard deviation of 5% of the average was adopted". In Dzotsi *et al.* (2013), who used the Simple SALUS model to simulate maize, peanut, and cotton, the ranges of parameter values were based on fitting the model to simulation results from a different model.

In a few cases, model calibration has been done by using a Bayesian or similar approach (Iizumi *et al.*, 2009; Wallach *et al.*, 2012; Wang *et al.*, 2005). In these cases, the parameter uncertainty is represented by the posterior distribution of the parameters, which is the result of combining prior knowledge (for example, from the literature) with the information in the data used for calibration. One can simultaneously estimate the posterior distribution of the variance of residual error. Then one has information about uncertainty due to model error as well as about uncertainty due to parameter uncertainty (Wallach *et al.*, 2012). Given the joint posterior distribution of parameters and model residual error, one can calculate the uncertainty for new situations from the same underlying population. Wallach *et al.* (2012) use this approach to calculate uncertainty in predicting the effects of different irrigation strategies.

It is much rarer to have tests of multiple alternative equations for the same overall model, but Koehler *et al.* (2013) do test various different temperature response functions within the GLAM model.

Uncertainty in model input variables (the usual input variables are weather, soil characteristics, management, and initial conditions) is another source of uncertainty in model predictions. A major source of uncertainty that is of primary interest in impact assessment is future weather. The effect of this uncertainty on yield predictions can be studied by running a crop model with the output from multiple climate models, as for example by Geethalakshmi *et al.* (2011) and Niu *et al.* (2009). Management under climate change is also uncertain, since this depends on development of new varieties, technological advances and adaptation measures. Another potentially important source of uncertainty is initial conditions. Crop models often require initial soil water and initial soil nitrogen as inputs. These inputs will depend on many factors, including weather during the years before the simulation. It might be possible to generate a distribution of possible values of initial conditions, but this has only recently been explored in the context of climate change studies (e.g., Ruane *et al.*, 2013).

There have recently been several studies in which multi-model ensembles of crop models have been used, and emphasis has been on the variability across the models as a measure of the uncertainty in predictions (Asseng *et al.*, 2013; Palosuo *et al.*, 2011; Rötter *et al.*, 2012).

Economic Models

In this section we briefly describe the types of economic models and how they are used in integrated assessment, and then discuss some issues related to assessing uncertainty in these models.

Types of economic models used for integrated assessment

A variety of economic models are used to assess climate impacts and adaptation for agriculture. These models vary widely in model type and scope, and in their spatial and temporal features. The various models require different input data as drivers; all make various assumptions regarding model structure (functional form, dynamics), and require parameter values for any given calibration and scenario. All of these dimensions introduce uncertainty into economic model projections.

Global agricultural market models are designed to simulate the behavior of market prices and production for major commodities (e.g., Nelson *et al.*, 2014a). Most of these models were originally designed to analyze trade and domestic policies and their economic impacts. These models represent economic processes in many different ways. Some models are partial equilibrium (PE; e.g., the IMPACT model), and solve for equilibrium in agricultural commodity markets, given other sectors' economic variables and by drawing incomes and input prices from scenarios which are determined outside of the model. Other models are computable general equilibrium (CGEs; e.g., the GTAP model) and solve for equilibrium in an entire economy (or the global economy) simultaneously. PE models can represent more detail in commodities (e.g., major crop and livestock species), whereas CGE models represent more aggregate commodities. The various models utilize different spatial units of analysis (e.g., subnational, national, multi-country regions). All of these models are large and complex, with many parameters that are either estimated econometrically or are assigned plausible values through a calibration process. These models incorporate the effects of climate change in various ways. Some utilize crop or livestock model yields as inputs (e.g., the IMPACT model uses DSSAT crop models; the GLOBIOM model utilizes the EPIC model), and some are linked to other environmental or resource process models (e.g., IMPACT is linked to a water resource model).

A second group of models are designed to represent market equilibrium at the national level (e.g., the FASOM model for the US), or regional (multi-country) level (e.g., the CAPRI model for the EU). These models typically provide a greater level of detail in terms of commodities, production inputs, spatial units, and may be linked to resource models (e.g., FASOM uses EPIC model data as input, and is linked to models that simulate forestry and environmental processes).

A third group of models used for impact assessment takes economic variables such as prices as givens (these can be taken from national or global market equilibrium models), and uses them as inputs along with other data (e.g., crop yields, climate data, various other biophysical and socio-economic variables such as farm characteristics) to simulate various types of economic outcomes such as land use, demand for inputs such as fertilizer and labor, crop and livestock production, land values, and economic returns. These models operate at various levels

of disaggregation, including agroecological zones (AEZ), river basins (or "food-producing units"), political units such as counties or districts, grid cells, and individual farms. The models represent decision-making in various ways as well; some are optimization models, designed to be solved for land allocation or production based on a specified objective such as profit or expected utility maximization; other models simulate decisions based on observed behavior that is embodied in econometrically estimated models, also typically based on profit maximization or expected utility maximization assumptions; and some are agent-based models that utilize some type of decision rule for individual economic agents.

Assessing uncertainty in global economic models

As with climate and crop models, we can define uncertainty in terms of model inputs, model structure, and model parameters. The methods described above, such as sensitivity analysis, Monte Carlo simulation, and the use of ensembles can also be used for economic models, at least in principle. However, in practice, the practicality of different types of uncertainty analysis differs substantially across the three types of models.

For the typically large, complex global models, with parameters derived from various sources, application of Monte Carlo simulation is difficult and has not been widely applied. Instead, most studies have used sensitivity analysis to evaluate the effect of parameters thought to play an important role in an analysis. For example, the AgMIP global economic model intercomparison exercise identified parameters that are related to land substitution between types of economic activities and certain commodity supply parameters to be important.

The AgMIP global model intercomparison was the first attempt to use the ensemble approach to evaluate global agricultural economic model uncertainty. As discussed by Nelson *et al.* (2014b) and von Lampe *et al.* (2014), this exercise revealed a number of methodological issues. First, the fact that there is not a large number of similar models raises questions about the legitimacy of interpreting the results as a meaningful representation of uncertainty. Second, even though the models all represent global agricultural markets in some form, the two major types of models (PE and CGE) are sufficiently different in the way they are implemented (e.g., the way that outputs are aggregated), so as to make comparison of even basic outputs such as "the price of wheat" difficult. Moreover, each type of model has been implemented in different ways by different modeling groups, by using different types of aggregation, different functional structures, etc.

Assessing uncertainty in national and regional models

The issues identified above for implementing ensembles of global models are even more severe for national and regional models. Whereas there are more than ten global

agricultural market models that could be used to create an ensemble, at the national or subnational (regional) level, it is rare for researchers to implement more than one or at most a few similar models. For example, in the US, the Economic Research Service of USDA has developed a national model called REAP (Regional Environment and Agricultural Programming model; Johansson *et al*., 2007) and another similar national model called FASOM (Forest and Agricultural Sector Optimization Model; Adams *et al*., 1996), has been used for climate impact assessment. A number of national of regional land-use models have been developed for the US, but for specific analyses. Each of these models operates on different spatial scales and uses different structures. Most of these models are sufficiently large and complex that using Monte Carlo simulation to study uncertainty would be difficult.

A special case worth mentioning in relation to uncertainty analysis is the TOA-MD model being used by the AgMIP regional teams. Because it is a relatively parsimonious model, it is possible to implement Monte Carlo simulation. It is also straightforward to implement sensitivity analysis with the TOA-MD model, as illustrated by recent applications (e.g., Antle, 2011).

Reporting and Communicating Uncertainty

Communication is the key link between the generation of information about the uncertainty of climate change impacts on future food security and how information is used by decision-makers. In reporting uncertainty, it is important to consider the intended audience and their understanding of uncertainty issues. The means of reporting and communication will likely be different for the science and stakeholder communities. The way uncertainty is communicated can have a substantial impact on understanding gained and interpretation of information and subsequent decision-making (Budescu *et al.*, 2010; Morton *et al.*, 2010), particularly with regard to climate change adaptation planning (i.e., Matthews *et al.*, 2008; McCrum, 2009).

Probability density function (PDF) and cumulative distribution function (CDF)

One representation of uncertainty in simulated results is a graph of the PDF of $Y - \hat{Y}$, where Y is the quantity of interest and $\hat{Y}$ is the simulated value (Fig. 4). A cumulative distribution function (CDF) shows the same information but on the Y axis is the cumulative probability that $Y - \hat{Y}$ is smaller or equal to x, i.e., $\mathrm{P}(Y - \hat{Y} \leq x)$.

Probability of exceedance plots show the probability of exceeding a given value. The probability of exceedance is closely related to the CDF since $P(Y - \hat{Y} > x) = 1 - P(Y - \hat{Y} \leq x)$.

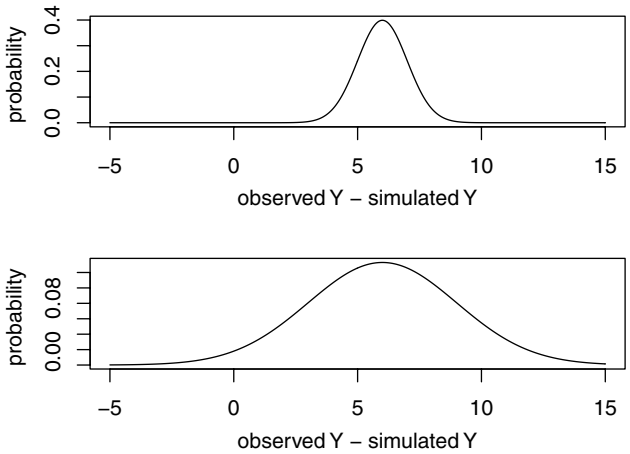


Fig. 4. Two probability density functions. The uncertainty represented in the top graph is smaller than that in the bottom graph.

Box plots

The box plot is a standard technique for presenting a summary of the distribution of a dataset. Box plots summarize several aspects of the PDF in a compact format. As Fig. 5 illustrates, the box plot shows the median, the 75th and 25th percentiles, and the 10th and 90th percentiles.

Box-plot modifications enable potentially more information to be conveyed, such as values outside the 10th and 90th percentiles, density indications that use the shape of the box sides to encode (i.e., histplot, vaseplot, box-percentile, and violin plot) data characteristics such as sample size and confidence levels; or additional statistics such as skewness and modality.

Impact response surfaces (*IRS*)

Impact response surfaces visualize two-dimensional explanatory variables and a response variable (Fronzek *et al.*, 2011, 2013). They can depict the sensitivity of impacts to climate change by showing the range of model behavior over a range of climate conditions. Note that these plots require assumptions of how to interpolate between the simulated values, for example, by creating a statistical fit over a region of the parameter space. One strength of IRS is that they allow a rapid visualization of model responses to small changes in conditions, for example, through climate model uncertainty or biases in observed datasets.

IRS are a major component of AgMIP's Coordinated Climate Crop Modeling Project (C3MP; Ruane *et al.*, 2014; see also Part 1, Chapter 8 in this volume) and are the emphasis of a work group in MACSUR. They have also been used with

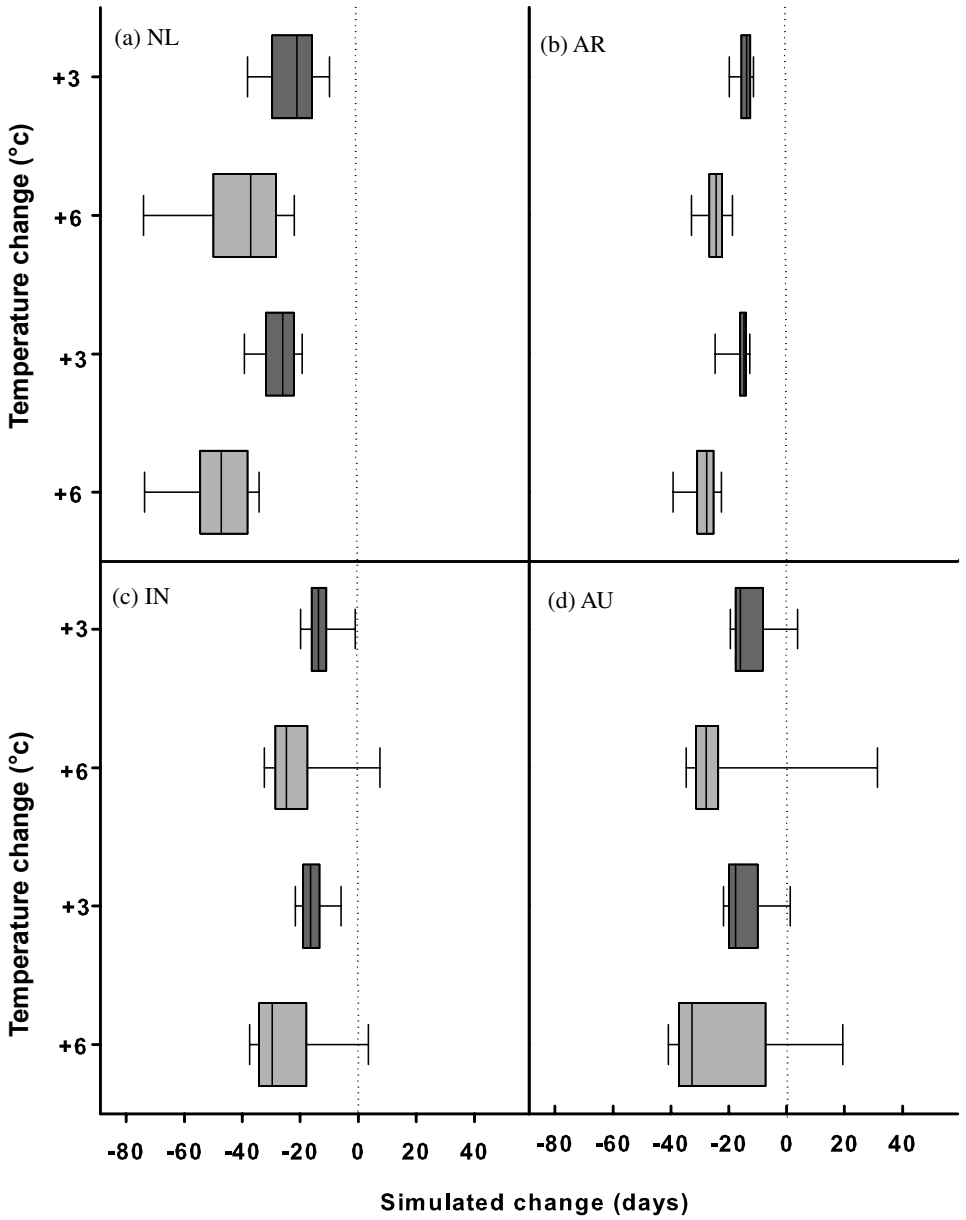


Fig. 5. Simulated change in anthesis (dark gray) and maturity (light gray) dates. Right-hand side of box = 75th percentile, left-hand side of box = 25th percentile, vertical line in box = median, right error bar = 90th percentile and left error bar = 10th percentile of simulations based on 24 models. NL = Netherlands, AR = Argentina, IN = India, AU = Australia. Reproduced by permission from Macmillan Publishers Ltd. [*Global Climate Change*]. (Asseng *et al.*, 2013). Copyright 2013.

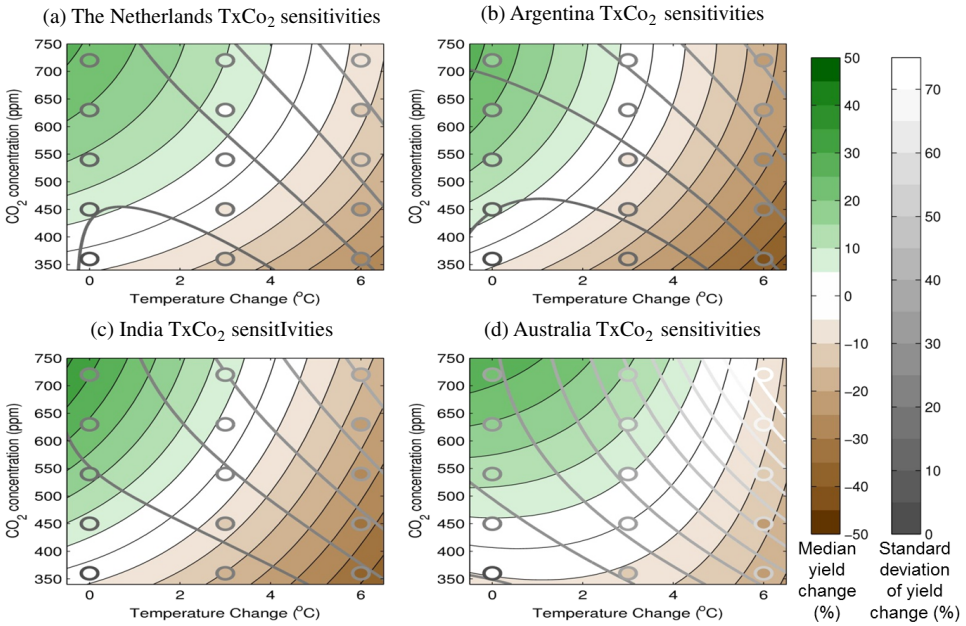


Fig. 6. Response surfaces of crop model ensemble to temperature and atmospheric CO_2 concentration sensitivity tests at (a) the Netherlands, (b) Argentina, (c) India, and (d) Australia. The filled colors represent the median (across the 26 models used) 30-year mean yield change (as a percentage of the mean 30-year yield for a 1981–2010 baseline period). The shade of the gray lines indicates the standard deviation (across the 26 models used) of the 30-year mean yield change (percentage of the 30-year mean baseline yield). Reproduced by permission from Macmillan Publishers Ltd. [*Global Climate Change*]. (Asseng *et al.*, 2013). Copyright 2013.

crop models to describe rice production in Japan (Iizumi *et al.*, 2010), sorghum and millet in West Africa (Sultan *et al.*, 2013), peanuts in the southeast US (Ruane *et al.*, 2014), and wheat in Australia (Howden *et al.*, 2005) and the Mediterranean region (Ferrise *et al.*, 2011).

Asseng *et al.* (2013), in the first AgMIP Wheat Intercomparison study, plotted wheat-yield change estimates from 26 crop models against temperature and CO_2 concentration changes. Because these models were all run at the same four locations, they were also able to overlay information of standard deviation of yield change to indicate uncertainty based on differences between models (Fig. 6).

Plume plots

Figure 7 is an example of a plume plot, which can display the temporal evolution of uncertainty, for example in probabilistic climate change projection data (i.e., UKCP, 2013).

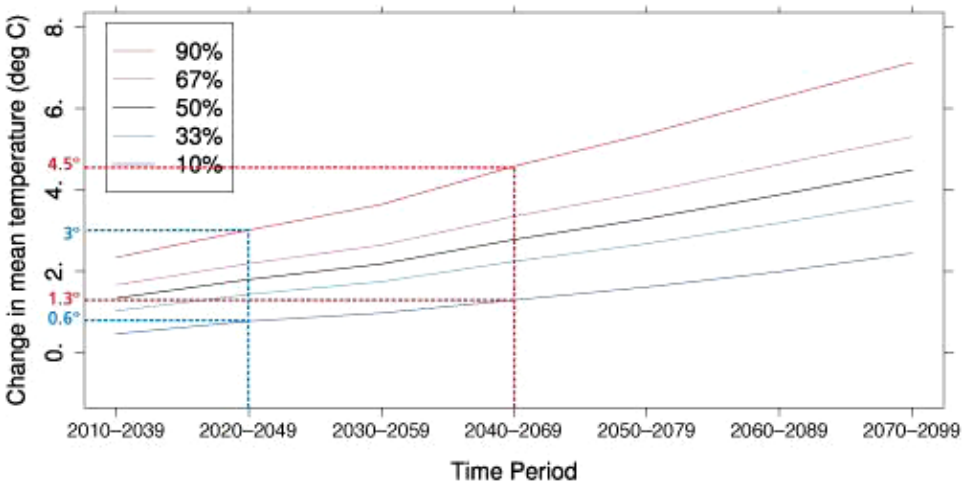


Fig. 7. In this plume plot the 80% confidence interval for mean temperature change over the 30-year period between 2020 and 2049 (2030s) is between 0.6 and 3°C (blue dashed lines) and 1.3 and 4.5°C in the period 2040–2069 (2050s; red dashed line) (UKCP, 2013), reproduced with permission.

Language-based reporting and communication methods

The IPCC uses a set of evidence and agreement statements that help provide a general text-based framework within which to express the level of uncertainty (Mastrandrea *et al.*, 2010). Confidence and uncertainty reporting in the IPCC AR5 is based on the author teams' evaluations of underlying scientific understanding. This is expressed as a qualitative level of confidence (from *very low* to *very high*) and, when possible, probabilistically with a quantified likelihood (from *exceptionally unlikely* to *virtually certain*). Confidence in the validity of a finding is based on the type, amount, quality, and consistency of evidence (e.g., data, mechanistic understanding, theory, models, expert judgment) and the degree of agreement (i.e., low, medium, and high). Probabilistic estimates of quantified measures of uncertainty in a finding are based on statistical analysis of observations or model results, or both, and expert judgment. Terms used to express expert judgment indicate the assessed likelihood of an outcome or a result: *virtually certain*, 99% to 100% probability; *very likely*, 90% to 100%; *likely*, 66% to 100%; *about as likely as not*, 33% to 66%; *unlikely*, 0% to 33%; *very unlikely*, 0% to 10%; *exceptionally unlikely*, 0% to 1%. Additional terms: *extremely likely*, 95% to 100%; *more likely than not,* >50% to 100%; *very unlikely*, 0% to 10%; and *extremely unlikely*, 0% to 5% can also be used (IPCC, 2013).

This means of communicating uncertainty, however, has come under criticism (e.g., Budescu *et al.*, 2009, 2014). It has been demonstrated, for example, that the American public misinterprets these verbal descriptions (Budescu *et al.*, 2009).

Apportioning Uncertainties

It is often of major interest to determine how much of the total uncertainty is contributed by each individual uncertainty source. This can help prioritize future research, which would be concentrated on the major contributions to overall uncertainty.

There is a large body of literature on the use of sensitivity analysis to apportion uncertainty among contributing sources (often called factors in the sensitivity literature) (Saltelli *et al.*, 2000), and many different approaches have been proposed.

A simple approach is to consider one factor at a time, by fixing all other factors at their nominal level. Bauer and Hamby (1991) proposed as a one-at-a-time sensitivity index the difference between the maximum and minimum values of the response when one factor is varied, divided by the maximal value of the response:

$$S_k = \frac{\max_{z_k} Y(\tilde{z}_1, \ldots, \tilde{z}_{k-1}, z_k, \tilde{z}_{k+1}, \ldots, \tilde{z}_K) - \max_{z_k} Y(\tilde{z}_1, \ldots, \tilde{z}_{k-1}, z_k, \tilde{z}_{k+1}, \ldots, \tilde{z}_K)}{\max_{z_k} Y(\tilde{z}_1, \ldots, \tilde{z}_{k-1}, z_k, \tilde{z}_{k+1}, \ldots, \tilde{z}_K)} \tag{6}$$

where $\tilde{z}_i$ is the nominal value of the ith factor.

Koehler *et al.* (2013) use a similar approach to compare the contributions of six different sources (different climate models, different data for calibration, different functions for temperature effect on development, different planting dates, different functions for lethal effect of temperature, different thresholds to describe temperature stress around anthesis) to uncertainty in yield. Their sensitivity index for the ith source is

$$\text{fractional uncertainty } i = \frac{\max_j(y_{ij}) - \min_j(y_{ij})}{\sum_i [\max_j(y_{ij}) - \min_j(y_{ij})]} \tag{7}$$

where y_{ij} is yield for the jth level of source i.

The variance-decomposition approach considers the variance of the simulated values as the summary measure of uncertainty, and examines how much of that variance is contributed by different sources.

The total variance of Y can be decomposed into terms that represent the effect of one factor at a time (the first-order sensitivity coefficients), interactions of two factors (second-order coefficients), etc. Often one calculates and reports only the first-order sensitivity coefficients S_i, which are defined as the variance of the conditional expectation of the output Y for fixed values of factor i, divided by the total variance of the output Y, that is:

$$S_i = \frac{\text{var}[E(Y|X_i)]}{\text{var}(Y)} \tag{8}$$

If there are no interactions, then the sum of the first-order sensitivity coefficients is 1.

Table 1. Calculation of first-order sensitivity coefficients.

Climate model	Crop model 1	Crop model 2	Crop model 3	Average over crop models
1	$\hat{Y}_{11}$	$\hat{Y}_{12}$	$\hat{Y}_{13}$	$(\hat{Y}_{11} + \hat{Y}_{12} + \hat{Y}_{13})/3$
2	$\hat{Y}_{21}$	$\hat{Y}_{22}$	$\hat{Y}_{23}$	$(\hat{Y}_{21} + \hat{Y}_{221} + \hat{Y}_{23})/3$
3	$\hat{Y}_{31}$	$\hat{Y}_{32}$	$\hat{Y}_{33}$	$(\hat{Y}_{31} + \hat{Y}_{32} + \hat{Y}_{33})/3$
Average over climate models	$(\hat{Y}_{11} + \hat{Y}_{21} + \hat{Y}_{31})/3$	$(\hat{Y}_{12} + \hat{Y}_{22} + \hat{Y}_{32})/3$	$(\hat{Y}_{13} + \hat{Y}_{23} + \hat{Y}_{33})/3$	The variance over the above three values is $S_{\text{climate model}} = \text{var}\,[E(Y\|\text{climate model})]$
	The variance over the above three values is $S_{\text{crop model}} = \text{var}\,[E(Y\|\text{crop model})]$			

First-order sensitivity coefficients can be used to apportion the uncertainty in simulations of the effect of climate change on crop yields. To illustrate, consider the case where crop yield under climate change, Y, is calculated by using three different crop models (Factor 1; see Table 1) and three different GCMs (Factor 2). The uncertainty in Y is taken as the variance of Y over the nine combinations of crop models and climate models. For each crop model, we take the average of Y over the three GCMs (bottom row). The variance over those three average values is the first-order sensitivity coefficient for the factor "crop model". The sensitivity for the factor "climate model" is the variance of the three values in the right-hand column.

The conclusions from such a study depend on what model output is studied. If, for example, one does not study yield directly, but rather yield change (future — baseline yield) then the values, the uncertainty, and the relative contributions to uncertainty will all change. If one studies relative yield change ((future — baseline yield)/baseline yield), the results will again differ.

A variance-based approach was also used to apportion the uncertainty in climate projections to uncertainty in internal climate variability, scenario uncertainty, and climate model uncertainty (Hawkins and Sutton, 2009). It was assumed that there is no interaction, so total variance is the sum of the variances due to each source. Figure 8 presents the combined effects of the three uncertainties for the CMIP5 models used in AR5. Note the important distinctions regarding the spatial scale (global vs. regional), the variable (temperature vs. precipitation) and the time-periods. Internal variability is most important in the near term for regional precipitation and least important for global annual mean temperature, when it ceases to account for variability after about 2075 due to the mean changes far exceeding the bounds of internal variability at such a large scale. The role of the concentration scenarios is most

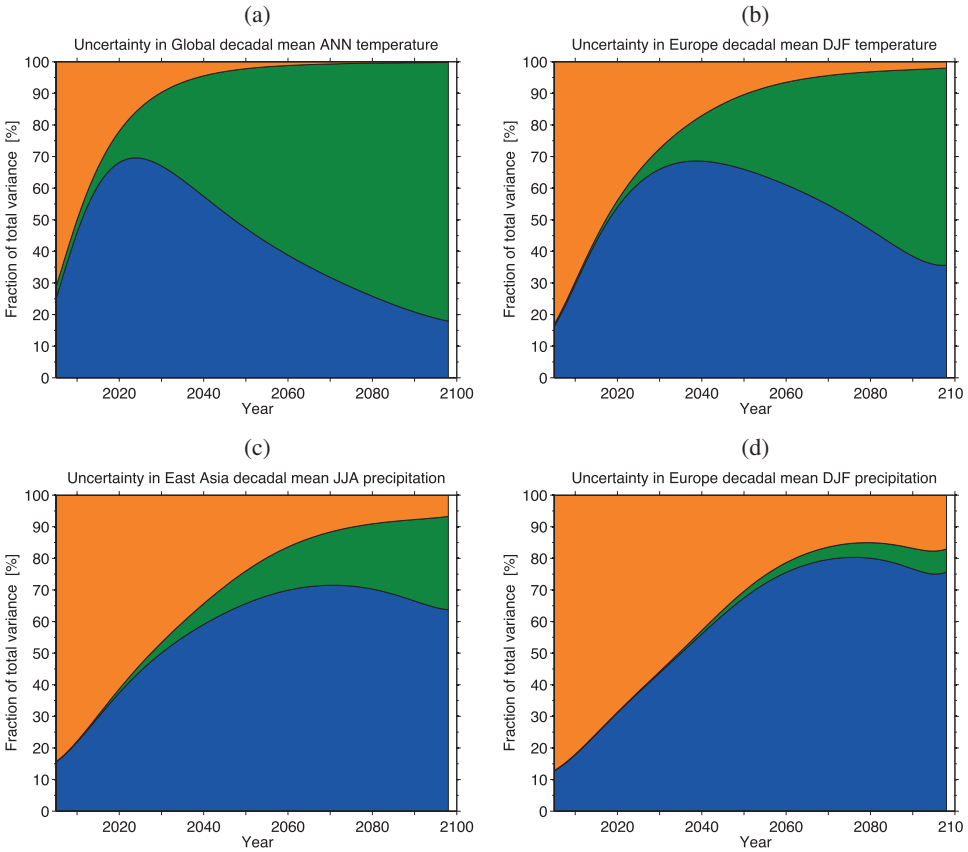


Fig. 8. Effect of different spatial and temporal scales on the relative contribution of different sources of uncertainty for temperature or precipitation in the CMIP5 simulations. (a) Global mean temperature, (b) winter temperature over Europe, (c) summer precipitation over East Asia, and (d) winter precipitation over Europe. Orange represents internal climate variability, green represents scenario uncertainty, and blue represents climate model uncertainty. Note the very large and persistent contribution of internal variability for regional precipitation in c and d. (Adapted from IPCC (2013), Chapter 11 (panels c, d, e, and f of original Figure 11.8), reproduced with permission.)

important for global mean temperature after the near-term decades. However, on the regional scale, the role of climate model uncertainty is also quite large for the mid-21st century until about 2080. For precipitation, the scenario effect is small throughout, and internal variability and climate model uncertainty dominate both on global and regional scales.

Future Directions

The overall objective of uncertainty analysis of model-based climate change impact assessment is to define and apply methods to quantify the end-to-end uncertainty,

and to apportion that uncertainty to specific causes. This is a major undertaking, and in practice must be broken down into manageable steps.

- How does the quality of the uncertainty estimate vary with the choice of crop models in the ensemble and the number of crop models? What can one say about how to choose crop models for the ensemble?
- In climate modeling, one creates super-ensembles by taking multiple models and for each model, multiple parameterizations or multiple initial conditions. Would the use of such super-ensembles improve the estimates of uncertainty for crop, livestock, or economic models?
- We have information about errors in hindcasts for each crop model. Should one take that into account in estimating uncertainty by multi-crop model ensembles? In which circumstances is this important? How should it be done?
- How good are estimates of uncertainty and how do we determine this?
- Using the average or median of crop model projections often gives good agreement with observations. What is the uncertainty of those ensemble predictors?
- In crop modeling, it seems to be difficult to go from uncertainty assessment to model improvement. How can we do better in identifying specific aspects of models that account for the uncertainty?
- How can we estimate uncertainty better in equilibrium economic models?
- How does climate uncertainty propagate downstream into crop and economic modeling components of integrated assessment?
- How can we determine model and parameter subsets that will make the best use of limited resources for multi-disciplinary, multi-model integrated assessment?
- How can we account for the uncertainty due to the factors not taken into account, such as pests and diseases?

One major issue is the current state of total uncertainty quantification for impact assessment. This should not be thought of as a single result, since the uncertainty depends on context; whether we are talking about impacts on farm or regional scales, whether detailed data for calibration are available or not, etc. We have detailed information about uncertainty in climate projections and also about uncertainty in crop model predictions/projections, and we are beginning to obtain information about uncertainty from impact studies involving multiple climate models providing input to multiple crop models. On the other hand, there seems to be much less information available about uncertainty in the estimation of the economic impact of climate change. The question then is how to combine the available information into estimates of the total uncertainty of impact assessments. This should also help identify the most important studies for improving the estimation of uncertainty.

It is already possible to identify a certain number of methodological topics where progress should help improve uncertainty estimation. The research questions posed

here primarily concern the use of multi-crop model ensembles for uncertainty estimation, since this is a recent development that will have a large impact.

References

Abedinpoura, M., Sarangib, A., Rajput, T. B. S., Pathak, H., and Ahmad, T. (2012). Performance evaluation of AquaCrop model for maize crop in a semi-arid environment, *Agric. Water Manage.*, **110**, 55–66.

Adams, D. M., Alig, R. J., Callaway, J. M., McCarl, B. A., and Winnett, S. M. (1996). *The Forest and Agricultural Sector Optimization Model (FASOM): Model structure and policy applications*, Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.

Aggarwal, P. K. (1995). Uncertainties in crop, soil and weather inputs used in growth models — implications for simulated outputs and their applications, *Agric. Syst.*, **48**, 36–384.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Bauer, L. R. and Hamby, D. M. (1991). Relative sensitivities of existing and novel model parameters in atmospheric tritium dose estimates, *Radiat. Prot. Dosimetry*, **37**(4), 253–260.

Bellocchi, G., Rivington, M., Donatelli, M., and Matthews, K. (2010). Validation of biophysical models: Issues and methodologies. A review, *Agron. Sustain. Dev.*, **30**, 109–130.

Ben Nouna, B., Katerji, N., and Mastrorilli, M. (2000). Using the CERES-Maize model in a semi-arid mediterranean environment. Evaluation of model performance, *Eur. J. Agron.*, **13**, 309–322.

Biernath, C., Gayler, S., Bittner, S., Klein, C., Högy, P., Fangmeier, A., and Priesack, E. (2011). Evaluating the ability of four crop models to predict different environmental impacts on spring wheat grown in open-top chambers, *Eur. J. Agron.*, **35**, 71–82.

Budescu, D. V., Broomell, S. B., and Por, H. H. (2009). Improving communication of uncertainty in the reports of the Intergovernmental Panel on Climate Change, *Psych. Sci.*, **20**, 299–308.

Budescu, D. V., Por, H.-H., Broomell, S. B., and Smithson, M. (2014). The interpretation of IPCC probabilistic statements around the world, *Nat. Clim. Change*, **6**, 508–512.

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., and Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation, *Nat. Clim. Change*, **4**(4), 287–291.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W. J., Johns, T., Krinner, G., Shongwe, M., Tebaldi, C., Weaver A. J., and Wehner, M. (2013). "Long-term Climate Change: Projections, Commitments and Irreversibility", in Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley P. M. (eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

Deser, C., Phillips, A., Bourdette, V., and Teng, H. (2010). Uncertainty in climate change projections: the role of internal variability, *Clim. Dynam.*, **38**(3–4), 527–546.

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S. (2012). Communication of the role of natural variability in future North American climate, *Nat. Clim. Change*, **2**(11), 775–779.

Dzotsi, K. A., Basso, B., and Jones, J. W. (2013). Development, uncertainty and sensitivity analysis of the simple SALUS crop model in DSSAT, *Ecol. Model.*, **260**, 62–76.

Ebi, K. L., Hallegate, S., Kram, T., Arnell, N., Carter, T., Edmonds, J., Krieglar, E., Mathur, R., O'Neill, B., Riahi, K., Winkler, H., Van Vuuren, D., and Zwickel, T. (2014). A new scenario framework for climate change research: background, process, and future directions, *Clim. Change*, **122**, 363–372.

Efron, B. (1983). Estimating the error rate of a prediction rule: improvement on cross-validation, *J. Am. Stat. Assoc.*, **78**, 316–331.

Efron, B. (1986). How biased is the apparent error rate of a prediction rule?, *J. Am. Stat. Assoc.*, **81**(394), 461–470.

Ferrise, R., Moriondo, M., and Bindi, M. (2011). Probabilistic assessments of climate change impacts on durum wheat in the Mediterranean region, *Nat. Hazards Earth Syst. Sci.*, **11**, 975–982.

Fronzek, S., Carter, T. R., and Luoto, M. (2011). Evaluating sources of uncertainty in modelling the impact of probabilistic climate change on sub-arctic palsa mires, *Nat. Hazards Earth Syst. Sci.*, **11**, 2981–2995.

Fronzek, S., Pirttioja, N. K., Luoto, M., Rötter, R. P., and Carter, T. R. (2013). Using impact response surfaces to evaluate sources of uncertainty in modelling climate change impacts, Impacts World 2013, International Conference on Climate Change Effects, 27–30 May 2013, Potsdam, Germany.

Geethalakshmi, V., Lakshmanan, A., Bhuvaneswari, K., Rajalakshmi, D., Sekhar, N. U., Anbhazhagan, R., and Gurusamy, L. (2011). Climate and agriculture: Model inter-comparison for evaluating the uncertainties in climate change impact assessment, *AGU Fall Meeting Abstracts*, **1**, 0935.

Giorgi, F. and Mearns, L. O. (2002). Calculation of best estimate, confidence, and uncertainty in regional climate changes from AOGCM simulations via the reliability ensemble averaging (REA)' method, *J. Clim.*, **15**, 1141–1158.

Giorgi, F. and Mearns, L. O. (2003). Probability of regional climate change calculated using the Reliability Ensemble Averaging (REA) Method, *Geophys. Res. Lett.*, **30**(12), 1629.

Giorgi, F., Jones, C., and Asrar, G. R. (2009). Addressing climate information needs at the regional level: The CORDEX framework, *WMO Bulletin*, **58**, 175–183.

Hawkins, E. and Sutton, R. (2009). The Potential to Narrow Uncertainty in Regional Climate Predictions, *Bull. Am. Meteorol. Soc.*, **90**(8), 1095–1107.

Hawkins, E. and Sutton, R. (2010). The potential to narrow uncertainty in projections of regional precipitation change, *Clim. Dynam.*, **37**(1–2), 407–418.

Howden, S. M. and Crimp, S. (2005). "Assessing dangerous climate change impacts on Australia's wheat industry", in Zerger, A. and Argent, R. M. (eds.), *MODSIM 2005 International Congress on Modelling and Simulation*, Modelling and Simulation Society of Australia and New Zealand, December 2005, pp. 170–176.

Iizumi, T., Nishimori, M., and Yokozawa, M. (2010). Diagnostics of climate model biases in summer temperature and warm-season insolation for the simulation of regional paddy rice yield in Japan, *J. Appl. Meteorol. Clim.*, **49**, 574–591.

Iizumi, T., Yokozawa, M., and Nishimori, M. (2009). Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: Application of a Bayesian approach, *Agric. Forest Meteorol.*, **149**(2), 333–348.

IPCC (2007a). *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L. (eds.), Cambridge University Press, Cambridge.

IPCC (2007b). *Climate Change 2007: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Parry, M., Canziani, O., Palutikof, J., van der Linden, P., and Hanson, C. (eds.), Cambridge University Press, Cambridge.

IPCC (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (eds.), Cambridge University Press, Cambridge.

Johansson, R., Peters, M., and House, R. (2007). Regional Environment and Agriculture Programming Model (REAP), USDA Economic Research Service, Technical Bulletin No. 1916.

Jones, R. N. (2000). Managing Uncertainty in Climate Change Projections — Issues for Impact Assessment, *Clim. Change*, **45**(3–4), 403–419.

Kim, Y., Katz, R. W., Rajagopalan, B., Podestà, G. P., and Furrer, E. M. (2012). Reducing overdispersion in stochastic weather generators using a generalized linear modeling approach, *Clim. Res.*, **53**, 13–24.

Knutti, R. (2010). The end of model democracy?, *Clim. Change*, **102**, 395–404.

Koehler, A.-K., Challinor, A. J., Hawkins, E., and Asseng, S. (2013). Influences of increasing temperature on Indian wheat: Quantifying limits to predictability, *Environ. Res. Lett.*, **8**(3), 034016.

Krause, P., Boyle, D. P., and Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment, *Adv. Geosci.*, **5**, 89–97.

Lempert, R., Nakicenovic, N., Sarewitz, D., and Schlesinger, M. (2004). Characterizing climate-change uncertainties for decision-makers. An editorial essay, *Climatic Change*, **65**(1/2), 1–9.

MacCracken, M. (2001). Prediction versus projection — forecast versus possibility, *WeatherZine*, **26**, 3–4.

Mastrandrea, M. D., Field, C. B., Stocker, T. F., Edenhofer, O., Ebi, K. L., Frame, D. J., Held, H., Kriegler, E., Mach, K. J., Matschoss, P. R., Plattner, G.-K., Yohe, G. W., and Zwiers, F. W. (2010). *Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties*. Intergovernmental Panel on Climate Change (IPCC). Available at: http://www.ipcc.ch. Accessed on 21 September 2014.

Matthews, K. B., Rivington, M., Buchan, K., Miller, D. G., and Bellocchi, G. (2008). Characterising and communicating the agro-meteorological implications of climate change scenarios to land management stakeholders, *Climate Research*, **35**, 59–75.

Maurer, E. P., Brekke, L., Pruitt, T., and Duffy, P. B. (2007). Fine-resolution climate projections enhance regional climate change impact studies, *Eos Trans. AGU*, **88**, 504.

Maurer, E. P., Wood, A. W., Adam, J. C., Lettenmaier, D. P., and Nijssen, B. (2002). A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States, *J. Climate*, **15**, 3237–3251.

McCrum, G., Blackstock, K., Matthews, K., Rivington, M., Miller, D., and Buchan, K. (2009). Adapting to climate change in land management: The role of deliberative workshops in enhancing social learning, *Environmental Policy and Governance*, **19**, 413–426.

Mearns, L. O., Bukovsky, M., Pryor, S. C., and Magana, V. (2013b). "Downscaling of climate information", in Ohring, G. (ed.) *Climate Change in North America*, Series in Regional Climate Studies, Springer, Swtizerland, pp. 201–250.

Mearns, L. O., Giorgi, F., Whetton, P., Pabon, D., Hulme, and Lal, M. (2003). *Guidelines for Use of Climate Scenarios Developed from Regional Climate Model Experiments*. Available at: http://www.ipcc-data.org/guidelines/dgm_no1_v1_10-2003.pdf. Accessed on 21 September 2014.

Mearns, L. O., Mavromatis, T., Tsvetsinskaya, E., Hays, C., and Easterling, W. (1999). Comparative responses of EPIC and CERES crop models to high and low spatial resolution climate change scenarios, *J. Geophys. Res.-Atmospheres*, **104**, 6623–6646.

Mearns, L. O., Sain, S., Leung, R., Bukovsky, M. S., McGinnis, S., Biner, S., Caya, D., Arritt, R. W., Gutowski, W., Takle, E., Snyder, M., Jones, R. G., Nunes, A. M. B., Tucker, S., Herzmann, D., McDaniel, L., and Sloan, L. (2013a). Climate change projections of the North American Regional Climate Change Assessment Program (NARCCAP), *Clim. Change Lett.*, **120**, 965–975.

Mkhabela, M. S. and Bullock, P. R. (2012). Performance of the FAO AquaCrop model for wheat grain yield and soil moisture simulation in Western Canada, *Agric. Water Manage.*, **110**, 16–24.

Morton, T., Rabinovich, A., Marshall, D., and Bretschneider, P. (2011). The future that may (or may not) come: How framing changes responses to uncertainty in climate change communications, *Global Environmental Change-Human and Policy Dimensions*, **21**, 103–109.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

Murphy, J. M., Booth, B. B. B., Boulton, C. A., Clark, R. T., Harris, G. R., Lowe, J. A., and Sexton, D. M. H. (2014). Transient climate changes in a perturbed parameter ensemble of emissions driven earth system model simulations, *Clim. Dynam.*

Murphy, J. M, Booth, B. B. B., Collins, M., Harris, G. R., Sexton, D. M. H., and Webb, M. J. (2007). A methodology for probabilistic predictions of regional climate change from perturbed physics ensembles, *Phil. Trans. Roy. Soc. A*, **365**, 1993–2028.

Nakocenovic, P. and Swart, R. (eds.) (2000). *Special Report on Emissions Scenarios*, Cambridge University Press, Cambridge.

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., Robinson, S., Schmid, E., Schmitz, C., Tabeau, A., and Willenbockel, D. (2014a). Climate change effects on agriculture: Economic responses to biophysical shocks, *Proc. Natl. Acad. Sci.*, **111**, 3274–3279.

Nelson, G. C., van der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., von Lampe, M., d'Croz, D. M., van Meijl, H., Müller, C., Reilly, J., Robertson, R., Sands, R. D., Schmitz, C., Tabeau, A., Takahashi, K., Valin, H., and Willenbockel, D. (2014b). Agriculture and climate change in global scenarios: why don't the models agree, *Agricultural Economics*, **45**, 85–101.

Niu, X., Easterling, W., Hays, C. J., Jacobs, A., and Mearns, L. (2009). Reliability and input-data induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in the U.S. Great Plains, *Agric., Ecosyst. Environ.*, **129**(1–3), 268–276.

Norton, J. P., Brown, J. D., and Mysiak, J. (2006). To what extent, and how, might uncertainty be defined? Comments engendered by "Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support": Walker *et al.*, Integrated Assessment 4: 1, 2003, *Integ. Assess. J.*, **6**, 83–88.

Palosuo, T., Kersebaum, K. C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., Patil, R. H., Ruget, F., Rumbaur, C., Takáč, J., Trnka, M., Bindi, M., Çaldağ, B., Ewert, F., Ferrise, R., Mirschel, W., Şaylan, L., Šiška, B., and Rötter, R. (2011). Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models, *Eur. J. Agron.*, **35**(3), 103–114.

Parker, W. S. (2013). Ensemble modeling, uncertainty and robust predictions, *Wiley Interdisc, Rev.: Clim. Change*, **4**(3), 213–223.

Pierce, D. W., Barnett, T. P., Santer, B. D., and Gleckler, P. J. (2009). Selecting global climate models for regional climate change studies, *Proc. Natl. Acad. Sci.*, **106**, 8441–8446.

Refsgaard, J. C., van der Sluijs, J. P., Hojberg, A. L., and Vanrolleghem, P. A. (2007). Uncertainty in the environmental modeling process — a framework and guidance, *Environ. Model. Software*, **22**, 1543–1556.

Richter, G. M., Acutis, M., Trevisiol, P., Latiri, K., and Confalonieri, R. (2010). Sensitivity analysis for a complex crop model applied to Durum wheat in the Mediterranean, *Eur. J. Agron.*, **32**(2), 127–136.

Rivington, M., Matthews, K. B., Bellocchi, G., and Buchan, K. (2006). Evaluating uncertainty introduced to process-based simulation model estimates by alternative sources of meteorological data, *Agric. Syst.*, **88**, 451–471.

Rivington, M., Miller, D., Matthews, K. B., Russell, G., Bellocchi, G., and Buchan, K. (2008). Downscaling Regional Climate Model estimates of daily precipitation, temperature and solar radiation data, *Clim. Res.*, **35**, 181–202.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., and Jones, J. W. (2013b). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison, *Proc. Natl. Acad. Sci.*, **111**, 3268–3273.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013a). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Rötter, R. P. (2014). Agricultural Impacts: Robust uncertainty, *Nat. Clim. Change*, **4**(4), 251–252.

Rötter, R. P., Carter, T. R., Olesen, J. E., and Porter, J. R. (2011). Crop–climate models need an overhaul, *Nat. Clim. Change*, **1**(4), 175–177.

Rötter, R. P., Palosuo, T., Kersebaum, K. C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., Olesen, J. E., Patil, R. H., Ruget, F., Takáč, J., and Trnka, M. (2012). Simulation of spring barley yield in different climatic zones of Northern and Central Europe: A comparison of nine crop models, *Field Crops Res.*,**133**, 23–36.

Roux, S., Brun, F., and Wallach, D. (2014). Combining input uncertainty and residual error in crop model predictions, *Eur. J. Agron.*, **52**, 191–197.

Ruane, A. C., Cecil, L. D., Horton, R. M., Gordón, R., McCollum, R., Brown, D., Killough, B., Goldberg, R., Greeley, A. P., and Rosenzweig, C. (2013). Climate change impact uncertainties for maize in Panama: Farm information, climate projections, and yield sensitivities, *Agric. Forest Meteorol.*, **170**, 132–145.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014b). AgMIP climate forcing data-sets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agric. Forest Meteorol.*, **170**, 132–145.

Ruane, A. C., McDermid, S., Rosenzweig, C., Baigorria, G. A., Jones, J. W., Romero, C. C., and Cecil, L. D. (2014a). Carbon–Temperature–Water change analysis for peanut production under climate change: A prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP), *Global Change Biol.*, **20**, 394–407.

Saltelli, A., Chan, K., and Scott, E. M. (2000). *Sensitivity Analysis*, Wiley, New York.

Santer, B. D., Taylor, K. E., Glecker, P. J., Bonfils, C., Barnett, T. P., Piere, D. W., Wigley, T. M. L., Mears, C., Wents, F. J., Briggemann, W., Gillet, N. P., Klein, S. A., Stolt, P. A., and Wehner, M. F. (2009). Incorporating model quality information in climate change detection and attribution studies, *Proc. Natl. Acad. Sci.*, **106**, 14778–14783.

Sexton, D. M. H. and Murphy, J. M. (2012). Multivariate probabilistic projections using imperfect climate models. Part II. Robustness of methodological choices and consequences for climate sensitivity, *Clim. Dynam.*, **38**, 2548–2558.

Sexton, D. M. H., Murphy, J. M., Collins, M., and Webb, M. J. (2011). Multivariate probabilistic projections using imperfect climate models part I: Outline of methodology, *Clim. Dyn.*, **38**, 2513–2542.

Soler, C. M. T., Sentelhas, P. C., and Hoogenboom, G. (2007). Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment, *Eur. J. Agron.*, **27**(2), 165–177.

Spiegelhalter, D. J. and Riesch, H. (2011). Don't know, can't know: Embracing deeper uncertainties when analysing risks, *Phil. Trans. Roy. Soc. A*, **369**, 4730–4750.

Sultan, B., Roudier, P., Quirion, P., Alhassane, A., Muller, B., Dingkuhn, M., and Baron, C. (2013). Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa, *Environ. Res. Lett.*, **8**(1), 014040.

Thrasher, B., Xiong, J., Wang, W., Melton, F., Michaelis, A., and Nemani, R. (2013). Downscaled climate projections suitable for resource management, *Eos Trans. AGU*, **94**, 321–323.

Tao, F., Zhang, Z., Liu, J., and Yokozawa, M. (2009). Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection, *Agric. Forest Meteorol.*, **149**(8), 1266–1278.

Tao, F. and Zhang, Z. (2010). Adaptation of maize production to climate change in North China Plain: Quantify the relative contributions of adaptation options, *Eur. J. Agron.*, **33**(2), 103–116.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design, *Bull. Am. Meteorol. Soc.*, **93**(4), 485–498.

Tebaldi, C., Smith, R., Nychka, D., and Mearns, L. O. (2005). Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multi-model ensembles, *J. Clim.*, **18**, 1524–1540.

Tebaldi, C. and Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections, *Phil. Trans. Roy. Soc.*, **365**, 2053–2075.

Thrasher, B., Xiong, J., Wang, W., Melton, F., Michaelis, A., and Nemani, R. (2013). Downscaled climate projections suitable for resource management, *Transactions American Geophysical Union*, **94**(37), 321–323.

UKCP (2013). *Interpreting plume plots*. Available at: http://ukclimateprojections.metoffice.gov.uk/22623. Accessed on 21 September 2014.

Van Vuuren, D. P., Kriegler, E., O'Neill, B. C., Ebi, K. L., Riahi, K., Carter, T. R., Edmonds, J., Hallegatte, S., Kram, T., Mathur, R., and Winkler, H. (2013). A new scenario framework for Climate Change Research: Scenario matrix architecture, *Clim. Change*, **122**(3), 373–386.

von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., d'Croz, D. M., Nelson, G. C., Sands, R. D., Schmitz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., and van Meijl, H. (2014). Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison, *Agric. Econ.*, **45**(1), 3–20.

Walker, W. E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M. B. A., Janssen, P., and Krayer von Krauss, M. P. (2003). Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support, *Integ. Assess.*, **4**(1), 5–17.

Wallach, D. Keussayan, N., Brun, F., Lacroix, B., and Bergez, J.-E. (2012). Assessing the uncertainty when using a model to compare irrigation strategies, *Agron. J.*, **104**, 1274–1283.

Wallach, D., Makowski, D., Jones, J. W., and Brun, F. (2014). *Working with Dynamic Crop Models*, 2nd Edition, Academic Press, London.

Wang, X., He, X., Williams, J. R., Izauralde, R. C., and Atwood, J. D. (2005). Sensitivity and uncertainty analysis of crop yields and soil organic Carbon simulated with EPIC, *Trans. ASAE*, **48**, 1041–1054.

Wilby, R. L., Charles, S., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. (2004). *Guidelines for use of climate scenarios developed from statistical downscaling methods*. Available at: http://www.ipcc-data.org/guidelines/dgm_no1_v1_10-2003.pdf. Accessed on 21 September 2014.

Wilks, D. S. (2012). Stochastic weather generators for climate-change downscaling, part II: Multivariable and spatially coherent multisite downscaling, *Wiley Interdiscip. Rev.: Clim. Change*, **3**(3), 267–278.

This page intentionally left blank

Chapter 10

Uncertainties in Scaling-Up Crop Models for Large-Area Climate Change Impact Assessments

Frank Ewert[1], Lenny G. J. van Bussel[1,20], Gang Zhao[1], Holger Hoffmann[1], Thomas Gaiser[1], Xenia Specka[2], Claas Nendel[2], Kurt-Christian Kersebaum[2], Carmen Sosa[3], Elisabet Lewan[3], Jagadeesh Yeluripati[4], Matthias Kuhnert[4], Fulu Tao[5], Reimund Rötter[5], Julie Constantin[6], Helene Raynal[6], Daniel Wallach[6], Edmar Teixeira[7], Balasz Grosz[8], Michaela Bach[8], Luca Doro[9], Pier Paolo Roggero[9], Zhigan Zhao[10], Enli Wang[10], Ralf Kiese[11], Edwin Haas[11], Henrik Eckersten[12], Giacomo Trombi[13], Marco Bindi[13], Christian Klein[14], Christian Biernath[14], Florian Heinlein[14], Eckart Priesack[14], Davide Cammarano[15], Senthold Asseng[15], Joshua Elliott[16], Michael Glotter[16], Bruno Basso[17], Guillermo A. Baigorria[18], Consuelo C. Romero[18], and Marco Moriondo[19]

[1]*Institute of Crop Science and Resource Conservation, Bonn, Germany*

[2]*Leibniz Centre for Agricultural Landscape Research, Müncheberg, Germany*

[3]*Swedish University of Agricultural Sciences, Uppsala, Sweden*

[4]*University of Aberdeen, Aberdeen, Scotland*

[5]*MTT Agrifood Research Finland, Mikkeli, Finland*

[6]*L'Institut national de la recherche agronomique, Auzeville, France*

[7]*Canterbury Agriculture & Science Centre, Lincoln, New Zealand*

[8]*Thünen-Institute of Climate-Smart-Agriculture, Braunschweig, Germany*

[9]*Univeristy of Sassari, Sassari, Italy*

[10]*Commonwealth Scientific and Industrial Research Organisation Land and Water, Canberra, Australia*

[11]*Karlsruhe Institute of Technology, Garmisch-Partenkirchen, Germany*

[12]*Swedish University of Agricultural Sciences, Uppsala, Sweden*

[13]*Dipartimento di Scienze delle Produzioni Agroalimentari e dell'Ambiente (DISPAA), Florence, Italy*

[14]*German Research Center for Environmental Health, Neuherberg, Germany*

[15]*University of Florida, Gainesville, FL, USA*

[16]*University of Chicago, Chicago, IL, USA*

[17]*Michigan State University, East Lansing, MI, USA*

[18]*University of Nebraska-Lincoln, Lincoln, NE, USA*
[19]*Institute of Biometeorology — National Research Council of Italy, Florence, Italy*
[20]*Wageningen University, Wageningen, the Netherlands*

Introduction

Problems related to food security and sustainable development are complex (Ericksen *et al.*, 2009) and require consideration of biophysical, economic, political, and social factors, as well as their interactions, at the level of farms, regions, nations, and globally. While the solution to such societal problems may be largely political, there is a growing recognition of the need for science to provide sound information to decision-makers (Meinke *et al.*, 2009). Achieving this, particularly in light of largely uncertain future climate and socio-economic changes, will necessitate integrated assessment approaches and appropriate integrated assessment modeling (IAM) tools to perform them. Recent (Ewert *et al.*, 2009; van Ittersum *et al.*, 2008) and ongoing (Rosenzweig *et al.*, 2013) studies have tried to advance the integrated use of biophysical and economic models to represent better the complex interactions in agricultural systems that largely determine food supply and sustainable resource use.

Nonetheless, the challenges for model integration across disciplines are substantial and range from methodological and technical details to an often still-weak conceptual basis on which to ground model integration (Ewert *et al.*, 2009; Janssen *et al.*, 2011). New generations of integrated assessment models based on well-understood, general relationships that are applicable to different agricultural systems across the world are still to be developed. Initial efforts are underway towards this advancement (Nelson *et al.*, 2014; Rosenzweig *et al.*, 2013).

Together with economic and climate models, crop models constitute an essential model group in IAM for large-area cropping systems climate change impact assessments. However, in addition to challenges associated with model integration, inadequate representation of many crops and crop management systems, as well as a lack of data for model initialization and calibration, limit the integration of crop models with climate and economic models (Ewert *et al.*, 2014). A particular obstacle is the mismatch between the temporal and spatial scale of input/output variables required and delivered by the various models in the IAM model chain.

Crop models are typically developed, tested, and calibrated for field-scale application (Boote *et al.*, 2013; see also Part 1, Chapter 4 in this volume) and short time-series limited to one or few seasons. Although crop models are increasingly used for larger areas and longer time-periods (Bondeau *et al.*, 2007; Deryng *et al.*, 2011; Elliott *et al.*, 2014) rigorous evaluation of such applications is pending. Among the different sources of uncertainty related to climate and soil data, model parameters, and structure, the uncertainty from methods used to scale-up crop models has received little attention, though recent evaluations indicate that upscaling of crop models for climate change impact assessment and the resulting errors and uncertainties deserve attention in order to advance crop modeling for climate change

assessment (Ewert *et al.*, 2014; Rötter *et al.*, 2011). This reality is now reflected in the scientific agendas of new international research projects and programs such as the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013) and MACSUR (MACSUR, 2014).

In this chapter, progress in evaluation of scaling methods with their related uncertainties is reviewed. Specific emphasis is on examining the results of systematic studies recently established in AgMIP and MACSUR. Main features of the respective simulation studies are presented together with preliminary results. Insights from these studies are summarized and conclusions for further work are drawn.

Methods of Scaling-Up Crop Models

Error versus uncertainty in scaling-up crop models

In crop modeling literature, the terms "error" and "uncertainty" are often used interchangeably (see Part 1, Chapter 9 in this volume). While error measures the deviation between simulated and past observations, uncertainty can be thought as a measure of the difference between simulated and likely future observations (see Part 1, Chapter 9 in this volume). While the relationship between past errors and future uncertainty is of critical importance, it is not the subject of this chapter. Here we focus on the scaling-up of crop models under past conditions that has resulted in errors that are largely unknown as many past studies have not justified, nor transparently disclosed, assumptions made in scaling models. Systematic evaluation of scaling methods should provide some understanding of the size of this error and hence help to quantify and reduce the uncertainty in applying crop models for large-area assessment in the future. We do not investigate future uncertainty in this chapter, but rather examine the errors produced, and their implications, of scaling-up crop models with historic climate/weather data. Likewise, the uncertainty of upscaling should be analyzed in conjunction with the uncertainties related to climate input data, crop model structure, and model parameters (Asseng *et al.*, 2013; Palosuo *et al.*, 2011; Rötter *et al.*, 2012), which is beyond the scope of this chapter.

Scales — resolution, extent, and coverage

The most relevant scales in crop modeling refer to space and time. Various terms are related to scales such as extent, resolution, and coverage though their exact meaning is often unclear and they are therefore defined and discussed again here following Bierkens *et al*. (2000), Ewert (2004), and van Delden *et al.* (2011; see also Fig. 1). Scale is defined as the characteristic dimension in time and space of a phenomenon or

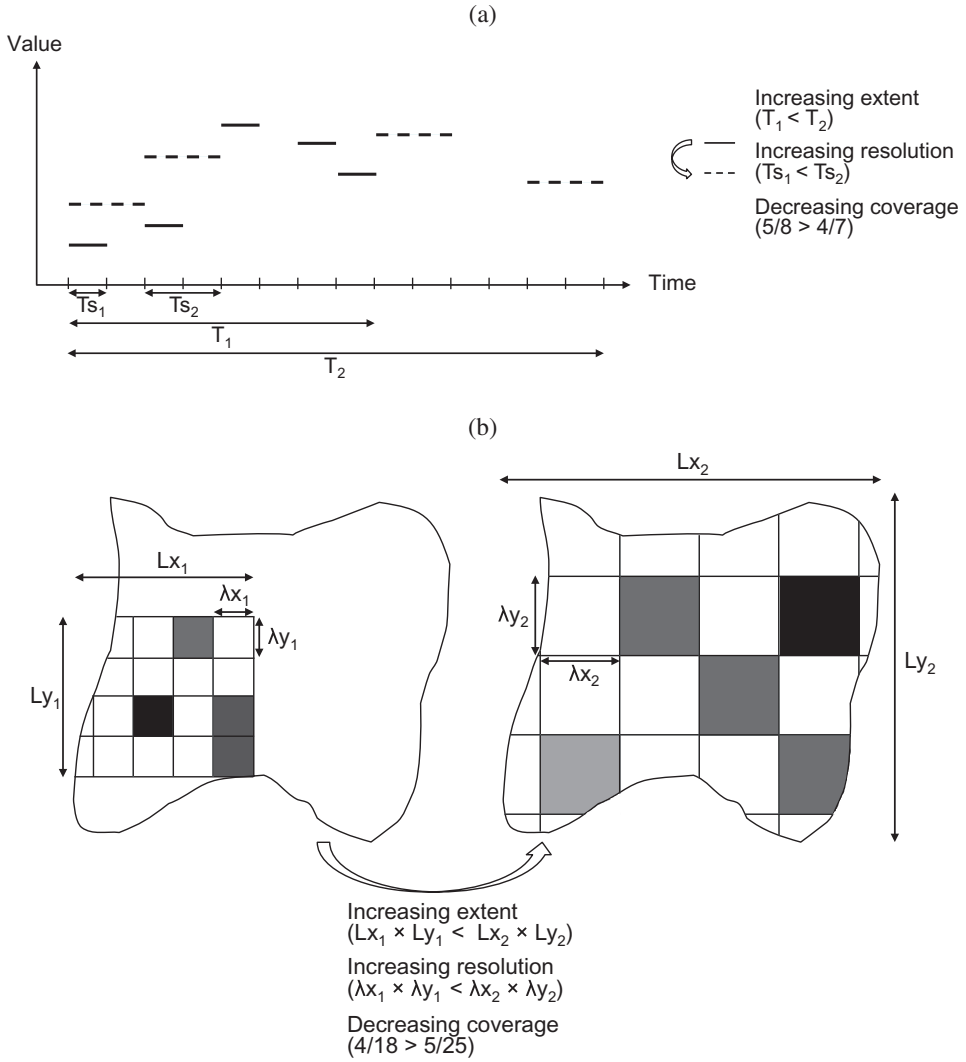


Fig. 1. Schematic representation of resolution, extent, and coverage for (a) spatial and (b) temporal scales. Increasing the spatial extent often means that the resolution becomes coarser (modified from Bierkens *et al*., 2000). Note that this study only refers to spatial upscaling.

observation, and thus dimensions and units of measurements can be assigned. In the context of this chapter, the definition of scale is colloquial (in contrast with the older cartographic definition of scale), which implies that large-scale studies deal with large extents, while small-scale studies are concerned with a small extent. Extent refers to the area and time-period over which the observations or simulations have

been made. Resolution indicates the largest spatial unit or time-period for which the variable of interest is considered to be homogeneous, i.e., only the average value of the variable is known, not the variation. A finer resolution indicates more observations per time or spatial unit, or, in the case of simulations, the use of a smaller grid size or time-step.

Coverage refers to the ratio between the sum of areas (or time-periods) for which the observations or simulations have been made and the extent (Fig. 1). Detail relates to the spatial and temporal resolution, as well as the complexity employed, in the representation of processes. Complexity is defined as the number of included relations and variables in a model. Finally, scaling is defined as transferring data and models between scales, a definition used by Blöschl and Sivapalan (1995), Ewert *et al*. (2011), and van Delden *et al*. (2011). Upscaling transfers data and models, including parameters, to a larger scale, while downscaling implies transfer of data, models, and parameters to a smaller scale. Scales should not be confused with levels of organization (Ewert *et al.*, 2011), which refer to organizational (or structural) entities such as a single plant organism, agroecosystem or farm, or the regional, national, continental, or global food system. These levels of organization have typical spatial extents and can be analyzed over specific time-periods.

Relevant processes of crop growth and yield should be modeled with sufficient functional detail, which will depend on the considered spatial and temporal resolutions. While appropriate model detail is increasingly viewed as important, the topic is still little understood (Adam *et al.*, 2011). Therefore, the use of the term "scale" implies that the application of a model refers to an area (or time-period) with a certain extent and that the model is used with a spatial and temporal resolution that should be concurrent to the resolution for which the model was originally developed. Any deviation from this will require proper evaluation (and perhaps modification of model structure, parameters, or input data) as the model is used outside the system characteristics for which it was originally developed.

Upscaling methods

While climate impact assessment studies are generally conducted on large scales, most crop models have been developed for a spatial resolution of a plot or homogenous field, with crop physiological processes typically simulated with daily temporal resolution. For some models (or processes), the resolution is higher — hours or even minutes. In theory, crop models can be applied to an infinite number of plots or homogenous fields as long as the required input data (weather, soil, and crop management) and cultivar parameters are available. The same applies to the temporal extent, i.e., the number of years for which the model is applied. In practice, large-scale model application is constrained by data availability and computing time

with relatively little consideration given to the mismatch in model process details and spatial scale of application. Therefore, methods to adjust (and likely reduce) model complexity with increasing scales are required.

Various methods are used to apply field models at larger scales, and generally are pragmatic solutions to the problem of limited data availability and/or computational power. For instance, model application in a region may be constrained to the (small) number of available weather stations from which data can be used for model simulations. Or, a model is applied in conjunction with climate change scenarios in which data are provided in grid cell format with a defined size, typically $50 \times 50\,\text{km}^2$ (e.g., Elliott *et al.*, 2014). The same applies to the temporal resolution of available climate/weather data, which may not have the resolution required for crop models (Nonhebel, 1994; van Bussel *et al.*, 2011). Such methods can be grouped according to how complexity is reduced. Accordingly, methods refer to the manipulation of (1) input data (climate, soil, management), (2) model structure, by reducing model complexity, and (3) model parameters. A comprehensive overview of scaling methods is given Ewert *et al.* (2011) and van Oijen *et al.* (2009). The most prominent methods used in climate change studies are described here.

Data aggregation, sampling, and extrapolation

Two main methods of data aggregation can be distinguished based on whether the aggregation refers to the input data or the output data after model simulation. The latter assumes that points are well sampled across a region to obtain good coverage. However, in most cases data coverage is insufficient. In the simplest case, only one so-called "representative" point is available within a region for which data (weather, soil, and crop management) are available and for which model simulations are performed. Simulation results for this point are then assumed to be representative for the entire region, i.e., simulations are extrapolated to all parts of the region (Fig. 2a). However, this is only valid if the region of concern is homogenous for all relevant input data of the model, which will rarely be the case. For heterogeneous regions, the number of sampling points should ideally be sufficient to represent the spatial heterogeneity in input data of this region. As information about the spatial variability in input data is limited, sampling points are usually randomly chosen. A more qualified way for considering heterogeneity within a region is stratified sampling (Fig. 2b). Sampling points are chosen for strata in a region that represent homogenous quantities, often climatic conditions. Hence, environmental stratifications are commonly used to support such sampling (Ewert *et al.*, 2011). However, the sampling is usually constrained by the number of available points with data. Little information is available about the relationship between change in number of sampling points and deviation in simulation results.

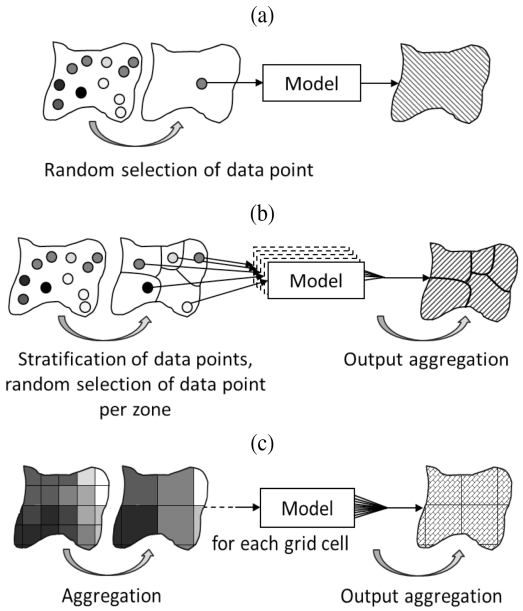


Fig. 2. Selected scaling methods often used in impact assessment studies: (a) extrapolation from a single point in the region to the entire region, (b) stratified sampling guided by an environmental stratification to sample points within relatively homogenous environmental strata, and (c) aggregation of input data to larger grid cells for which the models are run. For a more elaborated description of scaling methods see Ewert *et al*. (2011).

Alternatively, input data are aggregated and models are run with these aggregated input data (Fig. 2c), as is the case when models are used in combination with gridded climate data from climate models (Bondeau *et al.*, 2007; Deryng *et al.*, 2011; Elliott *et al.*, 2014). The main advantage of this method is that full coverage of the spatial extent of interest can be achieved. The disadvantage is that with increasingly coarse levels of aggregation, heterogeneity in input data is lost, which potentially affects simulation results as many processes in crop models are typically non-linear. Although both methods have frequently been used, uncertainties in using these methods are largely unknown. Further, possible interactions between scaling method and choice of crop model are unclear. Recent studies have pointed to the importance of using crop model ensembles in impact studies to account for the large uncertainty in crop models (Asseng *et al.*, 2013; Palosuo *et al.*, 2011; Rötter *et al.*, 2012).

Evaluating Uncertainty from Scaling Methods

Uncertainties in both methods of input and output data aggregation for model upscaling have been evaluated systematically in two comprehensive studies recently

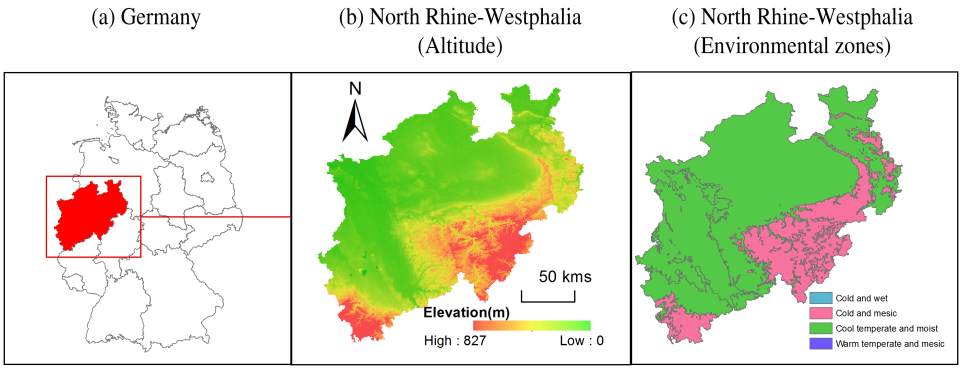


Fig. 3. Example region in (a) Germany used in scaling exercise. The region refers to the state of North Rhine-Westphalia with heterogeneous conditions of (b) altitude and (c) environmental conditions. Note that environmental zones are derived from Metzger *et al.* (2013).

launched within the international research program AgMIP (http://www.agmip.org/) and the FACCE JPI Knowledge Hub MACSUR (http://www.macsur.eu/). Simulation exercises and results are described in detail elsewhere for AgMIP (van Bussel *et al.*, 2014) and MACSUR (Hoffmann *et al.*, 2014; Zhao *et al.*, 2014). In these studies, the effect of different numbers of sampling points (AgMIP) and grid cell size (MACSUR) were investigated for winter wheat grown in the state of North Rhine-Westphalia in Germany (Fig. 3). The region was chosen because it is characterized by a considerable spatial heterogeneity in environmental (climate and soil) conditions (Fig. 3). Also, high-resolution weather and soil data were available.

Simulation exercises

Models were applied to simulate a typical winter wheat variety grown in the region. Information for model calibration only comprised a typical sowing date (October 1) and harvest date (August 1) and an indication of the regional average actual dry matter grain yield (about 7.2 t/ha) was given. Simulations were performed to obtain potential and water-limited yields. In the first step of these exercises the effect of scaling-up climate data was investigated. Other input data (soil, crop management) were kept constant. Hence, only one dominant soil type (sandy loam) with a rootable depth of 2.3 m and a total available water capacity of 429 mm was chosen for the entire region; more detailed soil information can be obtained from van Bussel *et al.* (2014). Also, crop management did not vary and was considered optimal for nitrogen fertilization and no effects of pests, diseases, or weeds were considered. Selected results presented in this chapter refer to potential growth, while results for

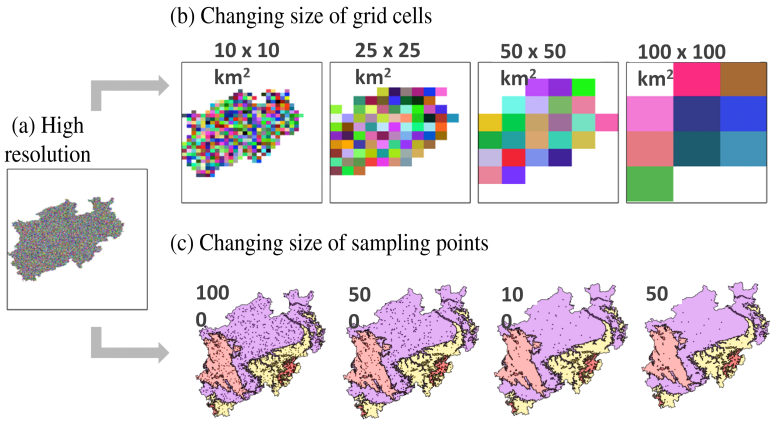


Fig. 4. Set-up of simulation experiments for evaluating deviations from (a) high-resolution simulations of (b) different grid cell sizes and (c) reduced numbers of sampling points. Details are described in van Bussel *et al.* (2014), Hoffmann *et al.* (2014), and Zhao *et al.* (2014).

water-limited conditions are shown elsewhere (Hoffmann *et al.*, 2014; van Bussel *et al.*, 2014; Zhao *et al.*, 2014).

In the AgMIP study 12 crop models were used (MONICA, APSIM, pDSSAT, HERMES, MCWLA, NWheat, SALUS, SIMPLACE<LINTUL2>, SPASS-ExpertN, STICS, CERES-wheat, and CROPGRO), a subset of those used in Asseng *et al*. (2013). Models and references are described in Asseng *et al*. (2013). Ten of the 12 models are considered in the later analysis described in this chapter. Five of these models were also used in the MACSUR study, along with six other models for a total of 11 models in this chapter (APSIM, Modified APSIM, COUP, DailyDayCent, LandscapeDNDC, EPIC, HERMES, SIMPLACE<LINTUL5>, MCWLA, MONICA, STICS). Models and references are described in Hoffmann *et al.* (2014) and Zhao *et al.* (2014).

The effect of different sample sizes (Fig. 2a, b) for climate/weather data were investigated in AgMIP; the number of sampling points per region was varied from 10, 100, 500, to 1000 points and compared with a high-resolution run for 34168 points (Fig. 4a), which refers to a 1×1 km^2 grid raster (Fig. 4c). The sampling of points was guided by the environmental stratification of Metzger *et al.* (2013). The effects of grid cell size was investigated in MACSUR by conducting simulations for the region with grid cell sizes of 10×10 km^2, 25×25 km^2, 50×50 km^2, and 100×100 km^2 (Fig. 4b). These were also compared with a high-resolution run from 100×100 km^2, i.e., 34168 cells. Observed actual yields were obtained from regional yield statistics (IT.NRW, 2014).

Impact of Scaling Method

Effect of sampling size (*AgMIP study*)

Surprisingly, differences in regional averages of simulated potential yields based on crop model ensemble means were small, depending on the number of sampling points considered (Fig. 5a). This was essentially consistent across models with differences between models for simulated yields larger than differences due to sample size (van Bussel *et al.*, 2014). The model ensemble mean also reproduced the interannual yield variability well for most years, again with small effects of sample size on temporal yield variability (Fig. 5b). As simulated yields refer to potential conditions they are about 15% to 20% higher than observed yields. Likewise, differences between models in simulating interannual yield variability were substantially larger than the small differences due to the different sample point sizes (van Bussel *et al.*, 2014). Such results suggest that with relatively few sample points (in this case ten) the relative error in regional yield simulations compared to simulations with a high density (full coverage) is small. However, our example referred to a stratified sampling case in which a sample size of ten points ensured that all environmental strata were sampled. Results may differ if points are sampled randomly without consideration of an environmental stratification (van Bussel *et al.*, 2014).

Effect of grid cell size (*MACSUR study*)

Simulation results of model ensemble means reveal some effects of changing grid cell sizes on potential yields (Fig. 5c). Average yields tend to decline as the size of the grid cells increases until a size of $50 \times 50\,\mathrm{km}^2$ (Fig. 5c). The higher average yield at the large grid cell size of $100 \times 100\,\mathrm{km}^2$ may be caused by the methodology of considering border grid cells, which results in a larger total area of this cell size as compared to smaller grid cell sizes. The ensemble mean of the 11 models used in this exercise also closely reproduced the interannual variability of observed regional yields (Fig. 5d). Again, model differences were considerable, as shown elsewhere (Hoffmann *et al.*, 2014; Zhao *et al.*, 2014). Grid cell size showed some effect on simulated potential yields, which changed depending on the year (Fig. 5d), but temporal patterns of ensemble means were not affected. These results suggest that for the crop, region, and models considered here, errors in simulating potential yields are comparably small for larger grid cell sizes. However, it should be noted that, also in this study, average potential yields were 15% to 20% higher than observed actual yields, which is in line with reported yield gaps for Germany.

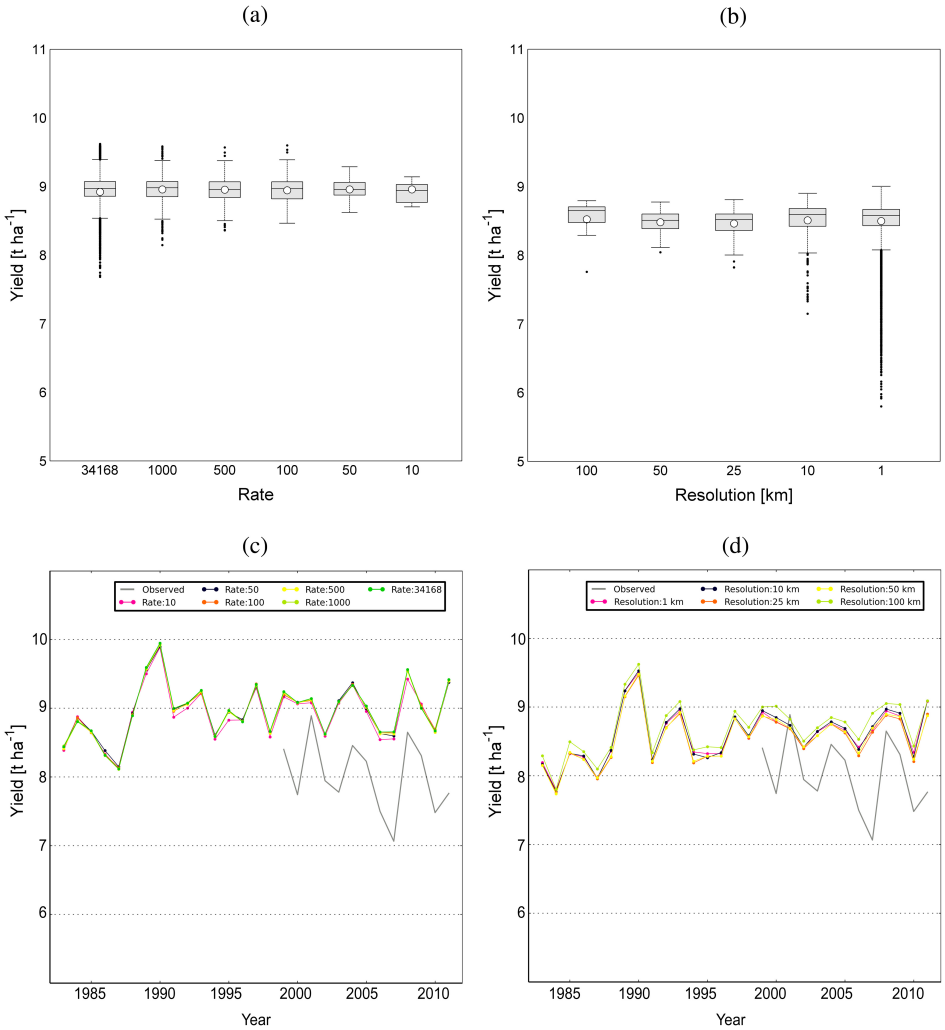


Fig. 5. Selected results from scaling exercise in AgMIP and MACSUR for simulated potential grain yield of winter wheat in North Rhine–Westphalia, Germany between 1981–2011. Results show model ensemble means of the effect of the number of sampling points (rate) on (a) 30-year yield statistics (box-and-whisker plots with mean, median, and 25th and 75th percentiles) and (b) interannual yield variability, and of the effects of grid cell size on (c) 30-year yield statistics (box-and-whisker plots with mean, median, and 25th and 75th percentiles) and (d) interannual yield variability. Gray lines in (b) and (d) refer to observed regional yield statistics. Note, different models are behind the ensemble means shown in the different panels (see the section on simulation exercises). For a more elaborated description and presentation of results see van Bussel *et al.* (2014), Hoffmann *et al.* (2014), and Zhao *et al.* (2014).

Spatial variability

Variability in simulated potential yield through space increases with increasing number of sample points (Fig. 5a) and decreasing grid cell size (Fig 5c). The effects of

climate/weather data aggregation on spatial variability have been reported earlier (Zhao *et al.*, 2015) and are also evident from this study (Zhao *et al.*, 2014). If information on the spatial variability of yields is required, studies based on few sample points or large grid cells may be insufficient. This applies particularly to areas where spatial variability in environmental conditions is high (Zhao *et al.*, 2015).

Knowledge Gaps and Future Activities

Knowledge gaps

These results (Fig. 5) are in line with a recent study (Angulo *et al.*, 2013) but contradict other studies (e.g., Hansen and Jones, 2000). The results presented here refer to potential yields and the aggregation of climate/weather data, though effects of scaling methods are more pronounced for water-limited yield (Hoffmann *et al.*, 2014; van Bussel *et al.*, 2014; Zhao *et al.*, 2014). It remains unclear how large the differences between the scaling methods with weather data become if regional variability in soil and management are considered and simulations are extended to also consider N-limited conditions. Likewise, there is no indication of to what extent results obtained in our studies can be transferred to other crops or regions. The results presented here refer to grain yield, whereas in integrated assessment studies other variables such as greenhouse gas emissions, N-leaching, N-yield will also be of interest (Ewert *et al.*, 2014). How transferable these results are across impacts variables is unknown. Particularly striking are the differences among crop models, not shown here but presented in detail elsewhere (Hoffmann *et al.*, 2014; van Bussel *et al.*, 2014; Zhao *et al.*, 2014). These which are consistent with reports from earlier studies (Asseng *et al.*, 2013) and are worth exploring in relation to the available input data for model calibration. As some interaction between scaling methods and crop models has been observed, such interactions should not be ignored in future studies. Ensemble means may be a suitable approach to avoid such interactions.

Future activities

Given these gaps, future research on better understanding the scaling-up of crop models for large-area assessments should focus on:

- Inclusion of spatial variability in soils.
- Consideration of spatial variability in management particularly for N fertilization, sowing dates, and varieties grown. A particular challenge is to understand the impact of methods to scale-up crop rotations (Teixeira *et al.*, 2014).

- Generalization of results across crops and regions.
- Adequate model structure, parameters, and use of ensemble means.

As these and other results suggest, given that uncertainty from crop models and global climate models (GCMs) is larger than from scaling methods applied to weather data input (with the qualification that soils and management variability has not been considered yet), future research should also focus on improving crop models for large-scale applications. Here the question of appropriate model detail becomes important (Adam *et al.*, 2011). To date, large-area crop models have not been developed to capture the relationships important at an aggregated regional scale. The same applies to long time-horizons.

The effect of upscaling may become more important if variability in soil and crop management is also considered. The latter is likely to be particularly relevant in regions where crop yields are more constrained by management than by climatic conditions and where spatial variability in management intensity is high. In regions with a large share of low-intensity farming systems as in Africa, crop physiological processes as considered in crop models may be less important (Webber *et al.*, 2014) than approaches of modeling effects of management. Hence, a new generation of crop models may be needed that adequately considers the range of factors and relations relevant at larger scales and that complies with the demands of integrated assessment modeling (IAM) (Ewert *et al.*, 2014).

Acknowledgements

Frank Ewert, Holger Hoffmann, and Lenny van Bussel acknowledge support from the FACCE MACSUR project (031A103B) funded through the German Federal Ministry of Education and Research. The work of Fulu Tao and Reimund Rötter was supported by the Academy of Finland, project NORFASYS (decision no 268277). The work of Carmen Sosa and Elisabet Lewan was supported by the Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning (FORMAS) and by strategic funding for research on "Soil, Water & Landscape" from the Faculty of Natural Resources and Agricultural Sciences (Swedish University of Agricultural Sciences). Christian Biernath was financed by the Helmholtz project "REKLIM — Regional Climate Change: Causes and Effects" Topic 9: "Climate Change and Air Quality". Christian Klein was financed by the project "GeoFarm — Precision Farming Systems" Work package 10: "Soil-Plant-Modelling". Florian Heinlein was financed by the DFG Research Group FOR 1695 "Agricultural Landscapes under Global Climate Change – Processes and Feedbacks on a Regional Scale". We thank the Landesbetrieb Information und Technik Nordrhein-Westfalen

for providing regional yield data, and the German Weather Service for providing weather data.

References

Adam, M., Van Bussel, L. G. J., Leffelaar, P. A., Van Keulen, H., and Ewert, F. (2011). Effects of modelling detail on simulated potential crop yields under a wide range of climatic conditions, *Ecol. Model.*, **222**, 131–143.

Angulo, C., Rötter, R., Trnka, M., Pirttioja, N., Gaiser, T., Hlavinka, P., and Ewert, F. (2013). Characteristic "fingerprints" of crop model responses to weather input data at different spatial resolutions, *Eur. J. Agron.*, **49**, 104–114.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Bierkens, M. F. P., Finke, P. A., and de Willigen, P. (2000). *Upscaling and downscaling methods for environmental research*, Kluwer, Dordrecht.

Blöschl, G. and Sivapalan, M. (1995). Scale issues in hydrological modelling: a review, *Hydrol. Proc.*, **9**, 251–290.

Bondeau, A., Smith, P. C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze Campen, H., Müller, C., and Reichstein, M. (2007). Modelling the role of agriculture for the 20th century global terrestrial carbon balance, *Global Change Biol.*, **13**, 679–706.

Boote, K. J., Jones, J. W., White, J. W., Asseng, S., and Lizaso, J. I. (2013). Putting mechanisms into crop production models, *Plant Cell Environ.*, **36**, 1658–1672.

Deryng, D., Sacks, W., Barford, C., and Ramankutty, N. (2011). Simulating the effects of climate and agricultural management practices on global crop yield, *Global Biogeochem. Cycle*, **25**, GB2006.

Elliott, J., Deryng, D., Müller, C., Frieler, K., Konzmann, M., Gerten, D., Glotter, M., Flörke, M., Wada, Y., Best, N., Eisner, S., Fekete, B. M., Folberth, C., Foster, I., Gosling, S. N., Haddeland, I., Khabarov, N., Ludwig, F., Masaki, Y., Olin, S., Rosenzweig, C., Ruane, A. C., Satoh, Y., Schmid, E., Stacke, T., Tang, Q., and Wisser, D. (2014). Constraints and potentials of future irrigation water availability on agricultural production under climate change, *Proc. Natl. Acad. Sci.*, **111**, 3239–3244.

Ericksen, P. J., Ingram, J. S., and Liverman, D. M. (2009). Food security and global environmental change: emerging challenges, *Environ. Sci. Policy*, **12**, 373–377.

Ewert, F. (2004). *Modelling changes in global regionalized food production systems under changing climate and consequences for food security and environment — development of an approach for improved crop modelling within IMAGE*, Wageningen University & Netherlands Environmental Assessment Agency (MNP), National Institute for Public Health and Environment (RIVM).

Ewert, F., Rötter, R. P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K. C., Olesen, J., van Ittersum, M. K., Janssen, S., Rivington, M., Semenov, M. A., Wallach, D., Porter, J. R., Stewart, D., Verhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P. P., Bartošová, L., and Asseng, S. (2014). Crop modelling for integrated assessment of climate change risk to food production, *Environ. Model. Software*, submitted.

Ewert, F., van Ittersum, M. K., Bezlepkina, I., Therond, O., Andersen, E., Belhouchette, H., Bockstaller, C., Brouwer, F., Heckelei, T., Janssen, S., Knapen, R., Kuiper, M., Louhichi, K., Olsson, J. A., Turpin, N., Wery, J., Wien, J. E., and Wolf, J. (2009). A methodology for enhanced flexibility of integrated assessment in agriculture, *Environ. Sci. Policy*, **12**, 546–561.

Ewert, F., van Ittersum, M. K., Heckelei, T., Therond, O., Bezlepkina, I., and Andersen, E. (2011). Scale changes and model linking methods for integrated assessment of agri-environmental systems, *Agric. Ecosyst. Environ.*, **142**, 6–17.

Hansen, J. W. and Jones, J. W. (2000). Scaling-up crop models for climate variability applications, *Agric. Syst.*, **65**, 43–72.

Hoffmann, H., Zhao, G., van Bussel, L., Enders, A., Xenia, S., Carmen, S., Jagadees, Y., Fulu, T., Julie, C., Edmar, T., Balasz, G., Luca, D., Zhigan, Z., Nendel, C., Kiese, R., Raynal, H., Eckersten, H., Haas, E., Wang, E., Kuhnert, M., Trombi, G., Bindi, M., Lewan, E., Bach, M., Kersebaum, K. C., Rötter, R., Roggero, P. P., Wallach, D., Krauss, G., Siebert, S., Gaiser, T., and Ewert, F. (2014). Effects of climate input data aggregation on modeling regional crop yields, *Clim, Res.*, in press.

IT.NRW (2014). *Statistik*. Available at: http://www.it.nrw.de/statistik/index.html. Accessed on 19 September 2014.

Janssen, S., Athanasiadis, I. N., Bezlepkina, I., Knapen, R., Li, H., Domínguez, I. P., Rizzoli, A. E., and van Ittersum, M. K. (2011). Linking models for assessing agricultural land use change, *Computer Electron. Agric.*, **76**, 148–160.

MACSUR (2014). Available at: http://www.macsur.eu/. Accessed on 21 September 2014.

Meinke, H., Howden, S. M., Struik, P. C., Nelson, R., Rodriguez, D., and Chapman, S. C. (2009). Adaptation science for agriculture and natural resource management — urgency and theoretical basis, *Curr. Opin. Environ. Sustain.*, **1**, 69–76.

Metzger, M. J., Bunce, R. G. H., Jongman, R. H. G., Sayre, R., Trabucco, A., and Zomer, R. (2013). A high-resolution bioclimate map of the world: A unifying framework for global biodiversity research and monitoring, *Global Ecol. Biogeog.*, **22**, 630–638.

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., Robinson, S., Schmid, E., Schmitz, C., Tabeau, A., and Willenbockel, D. (2014). Climate change effects on agriculture: Economic responses to biophysical shocks, *Proc. Natl. Acad. Sci.*, **111**, 3274–3279.

Nonhebel, S. (1994). The effects of use of average instead of daily weather data in crop growth simulation models, *Agric. Syst.*, **44**, 377–396.

Palosuo, T., Kersebaum, K. C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., Patil, R. H., Ruget, F., Rumbaur, C., Takac, J., Trnka, M., Bindi, M., Caldag, B., Ewert, F., Ferrise, R., Mirschel, W., Saylan, L., Siska, B., and Rötter, R. (2011). Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models, *Eur. J. Agron.*, **35**, 103–114.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Rötter, R. P., Carter, T. R., Olesen, J. E., and Porter, J. R. (2011). Crop-climate models need an overhaul, *Nat. Clim. Change*, **1**, 175–177.

Rötter, R. P., Palosuo, T., Kersebaum, K. C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., and Nendel, C. (2012). Simulation of spring barley yield in different climatic zones of Northern and Central Europe: a comparison of nine crop models, *Field Crop Res.*, **133**, 23–36.

Teixeira, E. I., Brown, H. E., Sharp, J. M., Meenken, E. D., and Ewert, F. (2014). Evaluating methods to simulate crop rotations for regional climate change assessments — a case study on the Canterbury plains of New Zealand, *Environ. Model. Software*, in press.

van Bussel, L. G. J., Ewert, F., Zhao, G., Hoffmann, H., Wallach, D., Klein, C., Biernath, C., Heinlein, F., Tao, F., Rötter, R., Cammarano, D., Asseng, S., Elliott, J., Glotter, M., Nendel, C., Basso, B., Baigorria, G. A., Romero, C. C., Kersebaum, K. C., Nendel, C., Specka, X., Gaiser, T., and Siebert, S. (2014). Spatial sampling of weather data for regional crop yield simulations, *Global Ecol. Biogeog.*, in press.

van Bussel, L. G. J., Müller, C., van Keulen, H., Ewert, F., and Leffelaar, P. A. (2011). The effect of temporal aggregation of weather input data on crop growth models' results, *Agric. Forest Meteorol.*, **151**, 607–619.

van Delden, H., van Vliet, J., Rutledge, D. T., and Kirkby, M. J. (2011). Comparison of scale and scaling issues in integrated land-use models for policy support, *Agric. Ecosyst. Environ.*, **142**, 18–28.

van Ittersum, M. K., Ewert, F., Heckelei, T., Wery, J., Alkan Olsson, J., Andersen, E., Bezlepkina, I., Brouwer, F., Donatelli, M., Flichman, G., Olsson, L., Rizzoli, A. E., van der Wal, T., Wien, J. E., and Wolf, J. (2008). Integrated assessment of agricultural systems - A component-based framework for the European Union (SEAMLESS), *Agric. Syst.*, **96**, 150–165.

van Oijen, M., Thomson, A., and Ewert, F. (2009). *Spatial upscaling of process-based vegetation models: An overview of common methods and a case-study for the U.K.*, StatGIS GeoInformatics for Environmental Surveillance., Milos Island, Greece, 17–19 June 2009., p. 6.

Webber, H., Gaiser, T., and Ewert, F. (2014). What role can crop models play in supporting climate change adaptation decisions to enhance food security in Sub-Saharan Africa?, *Agric. Syst.*, **127**, 161–177.

Zhao, G., Hoffmann, H., van Bussel, L., Enders, A., Xenia, S., Carmen, S., Jagadees, Y., Fulu, T., Julie, C., Edmar, T., Balasz, G., Luca, D., Zhigan, Z., Nendel, C., Kiese, R., Raynal, H., Eckersten, H., Haas, E., Wang, E., Kuhnert, M., Trombi, G., Bindi, M., Lewan, E., Bach, M., Kersebaum, K. C., Rötter, R., Roggero, P. P., Wallach, D., Krauss, G., Siebert, S., Gaiser, T., and Ewert, F. (2014). Impact of weather data spatial resolution on simulation of cropping systems: a comparison of models, production systems and crops, *Clim. Res.*, in press.

Zhao, G., Siebert, S., Rezaei, E. E., Yan, C., and Ewert, F. (2015). Demand for multi-scale weather data for regional crop modelling, *Agric. Forest Meteorol.*, 156–171.

This page intentionally left blank

Chapter 11

Statistical Analysis of Large Simulated Yield Datasets for Studying Climate Effects

David Makowski[1], Senthold Asseng[2], Frank Ewert[3], Simona Bassu[1], Jean-Louis Durand[4], Pierre Martre[5,6], Myriam Adam[7], Pramod K. Aggarwal[8], Carlos Angulo[3], Christian Baron[9], Bruno Basso[10], Patrick Bertuzzi[11], Christian Biernath[12], Hendrik Boogaard[13], Kenneth J. Boote[14], Nadine Brisson[1,11,#], Davide Cammarano[2], Andrew J. Challinor[15,16], Sjakk J. G. Conijn[17], Marc Corbeels[45], Delphine Deryng[19], Giacomo De Sanctis[11], Jordi Doltra[20], Sebastian Gayler[21], Richard Goldberg[22], Patricio Grassini[23], Jerry L. Hatfield[24], Lee Heng[25], Steven Hoek[13], Josh Hooker[26], Tony L. A. Hunt[27], Joachim Ingwersen[28], Cesar Izaurralde[29], Raymond E. E. Jongschaap[17], James W. Jones[2], Armen R. Kemanian[30], Christian Kersebaum[31], Soo-Hyung Kim[32], Jon Lizaso[33], Christoph Müller[34], Naresh S. Kumar[35], Claas Nendel[31], Garry J. O'Leary[36], Jorgen E. Olesen[37], Tom M. Osborne[38], Taru Palosuo[18], Maria V. Pravia[30,39], Eckart Priesack[12], Dominique Ripoche[11], Cynthia Rosenzweig[22], Alexander C. Ruane[22], Fredirico Sau[40], Mickhail A. Semenov[41], Iurii Shcherbak[10], Pasquale Steduto[42], Claudio Stöckle[43], Pierre Stratonovitch[41], Thilo Streck[28], Iwan Supit[44], Fulu Tao[45], Edmar I. Teixeira[46], Peter Thorburn[47], Denis Timlin[48], Maria Travasso[49], Reimund Rötter[18], Katharina Waha[34], Daniel Wallach[50], Jeffrey W. White[51], Jimmy R. Williams[52], and Joost Wolf[44]

[1]*L'Institut national de la recherche agronomique, Thiverval-Grignon, France*

[2]*University of Florida, Gainesville, FL, USA*

[3]*University of Bonn, Bonn, Germany*

[4]*Unité de recherche pluridisciplinaire sur la prairie et les plantes fourragères, Lusignan, France*

[5]*Genetic, Diversity and Ecophysiology of Cereals (GDEC), Clermont-Ferrand, France*

[6]*Blaise Pascal University, Aubière, France*

[7]*CIRAD, Montpellier, France*

[8]*CCAFS, New Delhi, India*

[9]*CIRAD, Montpellier, France*

[10]*Michigan State University, East Lansing, MI, USA*

[11] *L'Institut national de la recherche agronomique, Avignon, France*
[12] *German Research Center for Environmental Health, Neuherberg, Germany*
[13] *Centre for Geo-Information, Alterra, the Netherlands*
[14] *University of Florida, Gainesville, FL, USA*
[15] *University of Leeds, Leeds, UK*
[16] *International Centre for Tropical Agriculture (CIAT), Cali, Colombia*
[17] *Wageningen University and Research Centre, Wageningen, the Netherlands*
[18] *MTT Agrifood Research Finland, Mikkeli, Finland*
[19] *University of East Anglia, Norwich, UK*
[20] *Cantabrian Agricultural Research and Training Centre (CIFA), Muriedas, Spain*
[21] *University of Tübingen, Tübingen, Germany*
[22] *NASA Goddard Institute for Space Studies, New York, NY, USA*
[23] *University of Nebraska-Lincoln, Lincoln, USA*
[24] *National Laboratory for Agriculture and Environment, Ames, IA, USA*
[25] *International Atomic Energy Agency (IAEA), Vienna, Austria*
[26] *University of Reading, Reading, UK*
[27] *University of Guelph, Guelph, Ontario, Canada*
[28] *University of Hohenheim, Stuttgart, Germany*
[29] *Joint Global Change Research Institute, College Park, MD, USA*
[30] *Instituto Nacional de Investigación Agropecuaria (INIA), Treinta y Tres, Uruguay*
[31] *Leibniz Centre for Agricultural Landscape Research, Müncheberg, Germany*
[32] *University of Washington, Seattle, WA, USA*
[33] *Univ. Politécnica of Madrid, Madrid, Spain*
[34] *Potsdam Institute for Climate Impact Research, Potsdam, Germany*
[35] *Indian Agricultural Research Institute, New Delhi, India*
[36] *Landscape & Water Sciences, Department of Environment and Primary Industries, Horsham, Australia*
[37] *Aarhus University, Tjele, Denmark*
[38] *University of Reading, Reading, UK*
[39] *The Pennsylvania State University, University Park, PA, USA*
[40] *Univ. Politécnica of Madrid, Madrid, Spain*
[41] *Rothamsted Research, Harpenden, UK*
[42] *Food and Agriculture Organization of the UN (FAO), Rome, Italy*
[43] *Washington State University, Pullman, WA, USA*
[44] *Wageningen University, Wageningen, the Netherlands*

[45]*Chinese Academy of Science, Beijing, China*

[46]*The New Zealand Institute for Plant & Food Research Limited, Canterbury, New Zealand*

[47]*Commonwealth Scientific and Industrial Research Organisation (CSIRO) Ecosystem Sciences, Queensland, Australia*

[48]*United States Department of Agriculture, Agricultural Research Service (USDA-ARS), Beltsville, MD, USA*

[49]*Institute for Climate and Water, Castelar, Argentina*

[50]*Agrosystèmes et développement territorial (AGIR), Castanet-Tolosan, France*

[51]*Arid-Land Agricultural Research Center, Maricopa, AZ, USA*

[52]*Texas A&M University, TX, USA*

[#]*Dr. Nadine Brisson passed away in 2011 while this work was being carried out.*

This page intentionally left blank

Introduction

Many studies have been carried out during the last decade to study the effect of climate change on crop yields and other key crop characteristics. In these studies, one or several crop models were used to simulate crop growth and development for different climate scenarios that correspond to different projections of atmospheric CO_2 concentration, temperature, and rainfall changes (Semenov *et al.*, 1996; Tubiello and Ewert, 2002; White *et al.*, 2011). The Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013) builds on these studies with the goal of using an ensemble of multiple crop models in order to assess effects of climate change scenarios for several crops in contrasting environments.

These studies generate large datasets, including thousands of simulated crop yield data. They include series of yield values obtained by combining several crop models with different climate scenarios that are defined by several climatic variables (temperature, CO_2, rainfall, etc.). Such datasets potentially provide useful information on the possible effects of different climate change scenarios on crop yields. However, it is sometimes difficult to analyze these datasets and to summarize them in a useful way due to their structural complexity; simulated yield data can differ among contrasting climate scenarios, sites, and crop models. Another issue is that it is not straightforward to extrapolate the results obtained for the scenarios to alternative climate change scenarios not initially included in the simulation protocols. Additional dynamic crop model simulations for new climate change scenarios are an option but this approach is costly, especially when a large number of crop models are used to generate the simulated data, as in AgMIP.

Statistical models have been used to analyze responses of measured yield data to climate variables in past studies (Lobell *et al.*, 2011), but the use of a statistical model to analyze yields simulated by complex process-based crop models is a rather new idea. We demonstrate herewith that statistical methods can play an important role in analyzing simulated yield data sets obtained from the ensembles of process-based crop models. Formal statistical analysis is helpful to estimate the effects of different climatic variables on yield, and to describe the between-model variability of these effects.

These statistical methods can also be used to develop meta-models, i.e., statistical models that summarize process-based crop models, enabling scientists to explore the effects of new climate change scenarios. This approach is illustrated with two simulated yield datasets obtained by AgMIP for maize and wheat that were generated by using ensembles of process-based crop models. The yield datasets were used to develop a meta-model that provides a simplified representation of the original ensemble of crop models. The proposed meta-model is a statistical regression with random coefficients that describe the variability of the simulated yield data across the

original crop models. Once the statistical regression has been fitted to the simulated yield datasets, the meta-model can predict the effects of climate changes among the crop models and can thus be used to study alternative climate change scenarios that were not initially simulated. Finally, the results obtained with the meta-model were used to assess the risk of yield loss for maize and wheat as functions of temperature and CO_2 concentration change.

Materials and Methods

Simulated yield data

Yield data were simulated with 19 maize crop models and 26 wheat crop models in four contrasting sites for each species located in France (Lusignan), USA (Ames), Brazil (Rio Verde), and Tanzania (Morogoro) for maize, and in the Netherlands (Wageningen), Argentina (Balcarce), India (New Delhi), and Australia (Wongan Hills) for wheat.

Several climate scenarios were considered. For both species, four temperature changes (+0, +3, +6, +9°C) and five atmospheric CO_2 concentration changes (+0, +90, +180, +270, +360 ppm; where the baseline CO_2 concentration was set at 360 ppm) were considered over the 1980–2010 time-period. In addition, two precipitation changes (0% and −30%) were considered for maize and three rates of nitrogen fertilization (50%, 100%, and 150% of reference rates) were considered for wheat. The other scenarios were defined by combining temperature, CO_2 concentration, and precipitation changes. Thirty years of yield data were generated with each crop model for each of the climate scenarios (Figs. 1 and 2) and the simulated yield values were averaged over the years. Details of the maize and wheat protocols can be found in Bassu *et al.* (2014) and Asseng *et al.* (2013), respectively.

Statistical model

Simulated maize and wheat yield data were analyzed using two-level statistical random-effect models (Pinheiro and Bates, 2000). The following statistical model was used to analyze the maize yield data for each site separately:

Level 1, within crop model

$$\begin{aligned} Y_{ij} = {} & \alpha_{0i} + \alpha_{1i}\Delta T_{ij} + \alpha_{2i}\Delta T_{ij}^2 + \alpha_{3i}\Delta C_{ij} \\ & + \alpha_{4i}\Delta C_{ij}^2 + \alpha_{5i}\Delta C_{ij}\Delta T_{ij} + \alpha_{6i}\Delta R_{ij} + \varepsilon_{ij} \end{aligned} \quad (1)$$

where Y_{ij} is the 30-year mean yield simulated for the ith crop model (where $i = 1, \ldots, P$) and for the jth scenario (where $j = 1, \ldots, Q_i$). The variables ΔT_{ij}, ΔC_{ij},

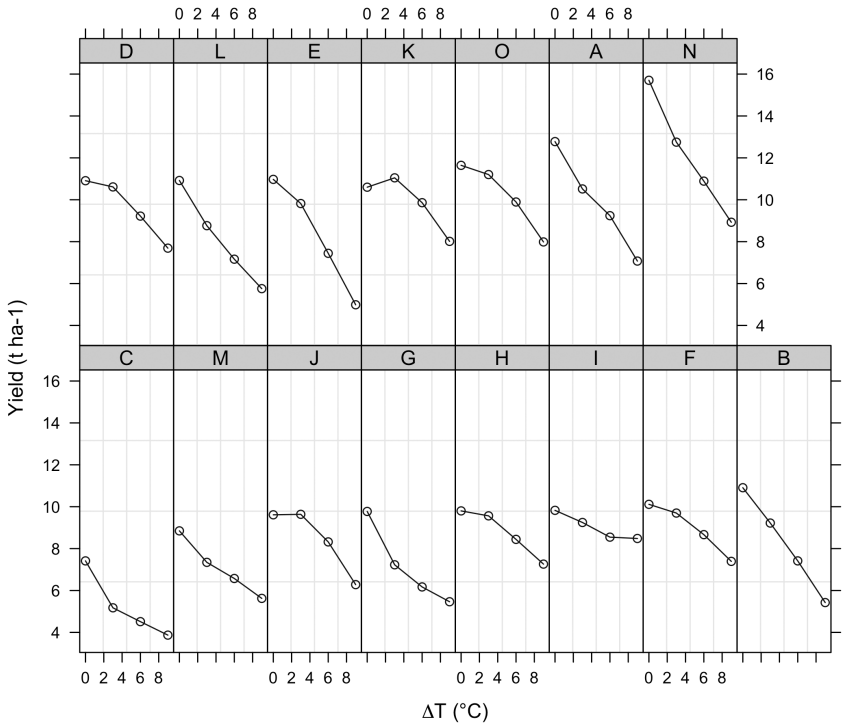


Fig. 1. Maize yields simulated by 15 crop models in Lusignan, France for different levels of temperature change (each letter corresponds to one crop model). The reported yield data were obtained for a change of CO_2 concentration equal to +180 ppm and for the baseline (1981–2010) level of precipitation. Only 15 out of the 19 available crop models simulated this level of [CO_2] and were thus included in the figure.

and ΔR_{ij} are the respective changes from the 1980–2010 baseline of temperature, atmospheric CO_2 concentration, and precipitation for model i and scenario j. The value of ε_{ij} is assumed to be independently and identically distributed such that $\varepsilon_{ij} \sim N(0, \tau^2)$ where τ^2 is the variance describing the residual error. The coefficients, α_{ki} (where $k = 0, \ldots, 6$), are seven random regression coefficients distributed according to independent Gaussian probability distributions.

Level 2, between crop models

$$\alpha_{ki} \sim N(\mu_k, \sigma_k^2), \quad k = 0, \ldots, 6 \tag{2}$$

The distribution parameters, μ_k (where $k = 0, \ldots, 6$), are the seven mean regression coefficient values that represent the mean yield baseline (μ_0) and mean effects of temperature, CO_2, temperature–CO_2 interaction, and rainfall ($\mu_1, \ldots, \mu_6$) over the P crop models. The seven variances, σ_k^2 (where $k = 0, \ldots, 6$), describe the between-model variability of the random regression coefficients.

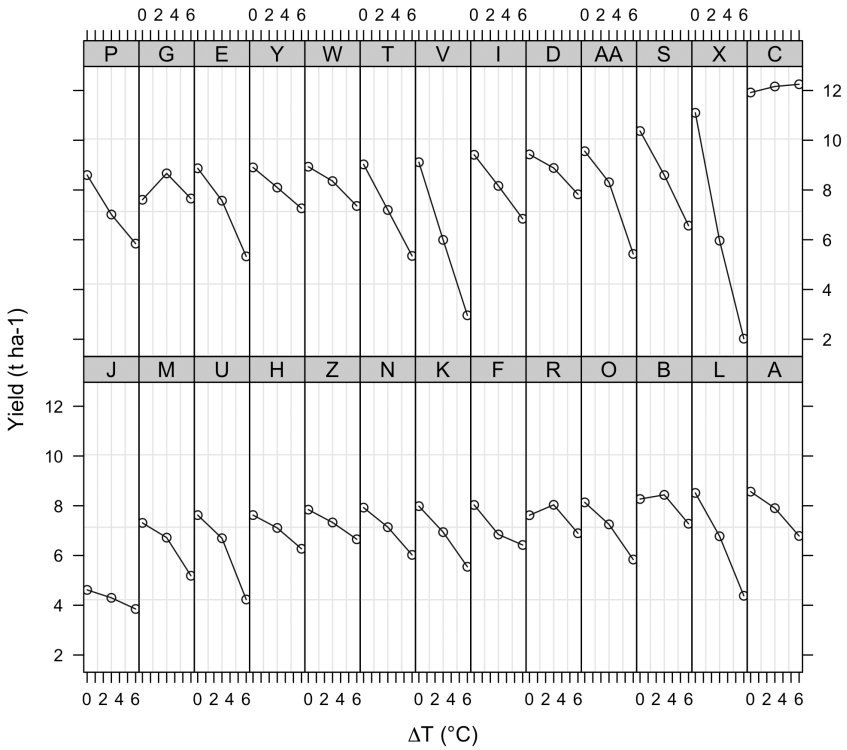


Fig. 2. Wheat yields simulated by the 26 crop models in Wageningen, the Netherlands, for different levels of temperature change (each letter corresponds to one crop model). The reported yield data were obtained for a change of CO_2 concentration equal to +180 ppm and for the baseline (1981–2010) level of fertilization.

This statistical model assumes that the ensemble of P crop models is a sample taken within a population that includes all possible crop models for a given crop while flexibly allowing for the incorporation of additional crop models in the future. The probability distributions defined by Equation (2) describe the between-crop-model variability of the yield response to climate change within the whole population of crop models. These probability distributions cover the ranges of climate effects considered in different crop models. The relationship defined by Equation (1) is assumed to be valid for all crop models, but its parameters, α_{ki}, are assumed to vary among crop models. However, this statistical model only describes 30-year mean yield responses and is not intended to describe the year-to-year variability of crop yields. Creating a statistical model that captured year-to-year variability would have required extra random terms and additional parameters, which would have overly complicated the calculated model and thus was not considered here.

The same form of model was used for wheat as was used for maize, but replaced the rainfall variable, ΔR_{ij}, with a variable that describes the level of N fertilization

in Equation (1). For the wheat pilot studies, precipitation was held constant in the wheat simulation protocol.

The population parameters of the statistical model μ_k, σ_k^2, and τ^2 were estimated by restricted maximum likelihood. The model-specific regression coefficients, α_{ki} (where $k = 0, \ldots, 6$ and $i = 1, \ldots, P$), were estimated by using the best linear unbiased predictor using the R software package "nlme" (Pinheiro and Bates, 2000) and the estimated values will be henceforth referred to as α_{eki}. The model was fitted for each crop and each site separately, but was calculated for all crop models together. Results were analyzed site by site.

Assessment of the statistical model

The statistical model was compared to other statistical models, including models with fewer explanatory variables, models with fewer random coefficients, and a model that includes no random coefficients (i.e., classical linear regression). All the models were compared by using the Akaïke information criterion (AIC; Pinheiro and Bates, 2000), where a lower AIC value corresponds with the better model, and we found that the model defined by Equations (1) and (2) led to lower AICs than the simpler models. The assumption that the residual errors, ε_{ij}, were independent was assessed by developing another statistical model that incorporated correlated residual errors. The AIC value of this model was higher and the estimated correlation coefficients were very low (7.6×10^{-4} and -4.7×10^{-3} for maize and wheat, respectively). The statistical model's quality of fit was also assessed by using graphical analysis. Evaluating the residuals did not reveal any obvious biases due to the assumptions made on the relationships between yields and input factors.

Estimation of the effect of climate change on yield

The statistical model described above was used to compute three different types of outputs:

- The average yield loss/gain due to climate change over the ensemble of crop models.
- The yield gain/loss estimated for individual crop models due to changes in climate variables.
- The probability that the yield loss/gain will exceed a given threshold.

For maize, the average yield difference obtained between a given climate change scenario (characterized by ΔT, ΔC, and ΔR) and the baseline scenario was expressed as:

$$\Delta Y = \mu_1 \Delta T + \mu_2 \Delta T^2 + \mu_3 \Delta C + \mu_4 \Delta C^2 + \mu_5 \Delta C \Delta T + \mu_6 \Delta R \qquad (3)$$

The yield difference described in Equation (3) is averaged over all crop models; this difference corresponds to an average yield gain or to an average yield loss over the 19 submitted crop models. Equation (3) defines a meta-model that simulates the average output of the original ensemble of crop models. This meta-model enables the computation of the yield differences for any changes in temperature, CO_2, and precipitation, ΔT, ΔC, and ΔR, at each of the four considered sites.

For a given crop model i, the yield difference was expressed as:

$$\Delta Y_i = \alpha_{e1i}\Delta T + \alpha_{e2i}\Delta T^2 + \alpha_{e3i}\Delta C + \alpha_{e4i}\Delta C^2 + \alpha_{e5i}\Delta C\Delta T + \alpha_{e6i}\Delta R \quad (4)$$

Equation (4) defines a meta-model simulating the output of the ith crop model. The yield difference (4) is crop model-specific. It corresponds to the climate change effect on yield that would have been obtained with the ith crop model if this crop model were run for a climate change scenario that were characterized by ΔT, ΔC, and ΔR.

The statistical model defined by Equations (1) and (2) was also used to compute the probability that the yield difference will exceed a threshold and, more specifically, the probability of yield gain or of yield loss that results from a change in the temperature, CO_2 concentration, and/or precipitation. This probability was computed from the following Gaussian probability distribution $N(\mu_{\Delta Y}, \sigma^2_{\Delta Y})$ as:

$$\mu_{\Delta Y} = \mu_1\Delta T + \mu_2\Delta T^2 + \mu_3\Delta C + \mu_4\Delta C^2 + \mu_5\Delta C\Delta T + \mu_6\Delta R \quad (5)$$

$$\sigma^2_{\Delta Y} = \sigma^2_1\Delta T^2 + \sigma^2_2\Delta T^4 + \sigma^2_3\Delta C^2 + \sigma^2_4\Delta C^4 + \sigma^2_5\Delta C^2\Delta T^2 + \sigma^2_6\Delta R^2 \quad (6)$$

Similar relationships were derived for wheat by replacing precipitation change with fertilization change in Equations (3) to (6). Note that the variance defined by Equation (6) is not constant but varies as a function of the climate scenario characteristics.

Results and Discussion

Increases in temperature

Figure 3 shows the statistical meta-models' quality of fit calculated for maize and wheat (one site per crop). The distributions of the residuals for both maize and wheat are symmetric and do not display trends. The fitted values obtained with the statistical meta-models are in most cases close to the yields simulated by the processed-based crop models. The residual standard error of the fitted statistical models is equal to 0.19 and 0.22 t/ha for maize and wheat, respectively, in the two sites considered in Fig. 3. A similar quality of fit was obtained for the other sites.

Figure 4 shows the change in the mean yield from the baseline for one maize site (Fig. 4a) and one wheat site (Fig. 4b) as affected by a CO_2 concentration increase

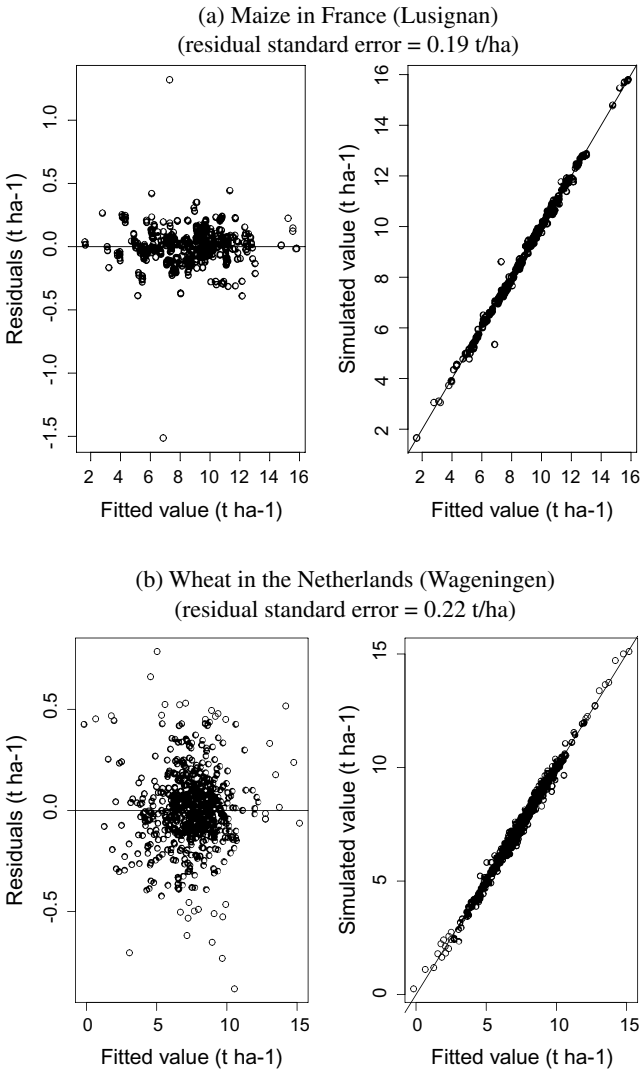


Fig. 3. Residuals of the statistical model and simulated versus fitted values obtained for (a) maize, and (b) wheat (one site per crop, all scenarios). The graphics compare yield values simulated by the crop models and yield values fitted by the statistical model for all scenarios.

of 180 ppm ($[CO_2] = 540$ ppm) and an increase in mean seasonal temperature ranging from 0°C to 6°C. Each emulated model yield as calculated by using the crop model-specific coefficients α_{eki} (where $k = 0, \ldots, 6$ and $i = 1, \ldots, P$) is plotted with a black line and thus can be seen as a proxy of a given crop model. Negative yield differences can be interpreted as mean yield losses and, conversely, positive yield differences can be interpreted as mean yield gains without the need

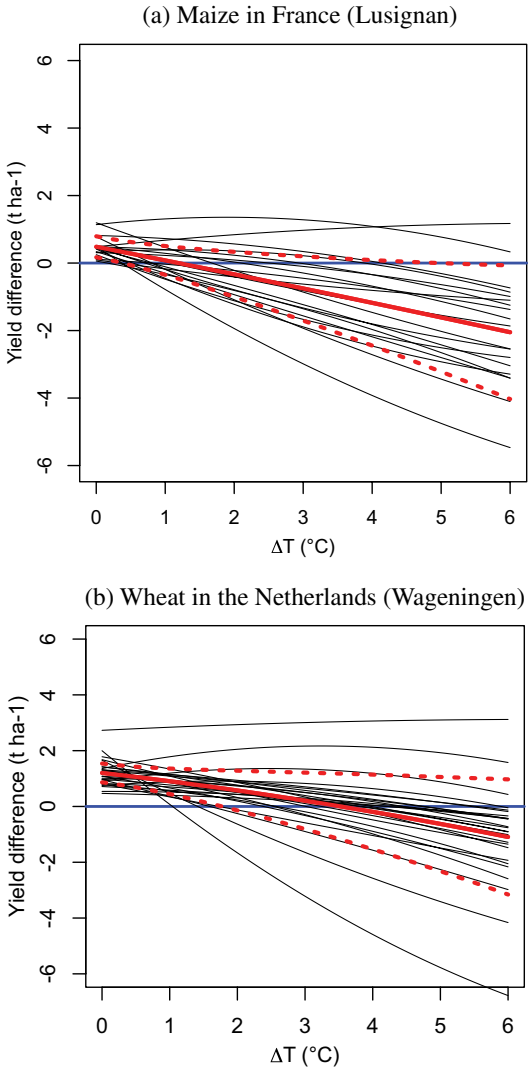


Fig. 4. The effect of climate change on yield for a CO_2 concentration increase of 180 ppm, and for mean temperature increases ranging from 0 to 6°C. Results are reported for (a) maize, and (b) wheat for one site per crop. Yield difference = yield obtained with a climate change scenario − yield obtained with the baseline (1981–2010). Each black curve corresponds to a given crop model. Black curves were obtained with the statistical model by using the crop model-specific coefficients α_{eki} (where $k = 0, \ldots, 6$ and $i = 1, \ldots, P$). The continuous red curve indicates the mean yield response as compared to the baseline scenario, i.e., the effect averaged over all crop models. The red dashed curves indicate the first and third quartiles of climate change effect computed over all crop models. The blue line indicates zero yield difference.

for re-running the original, process-based crop model. The continuous red curve indicates the mean yield response to the given climate scenario as compared to the baseline, i.e., the effect averaged over all crop models. The red dashed curves indicate the first (probability = 0.25) and third (probability = 0.75) quartiles of the climate change effect.

According to Fig. 4, most of the crop models estimate that a temperature increase negatively impacts yield projections of both maize and wheat in all locations. But this effect is highly variable among crop models, with some models predicting little response to temperature. For maize, Fig. 4a illustrates how, on average across the ensemble of crop models, the statistical meta-model emulates a yield loss when temperatures exceed +1.5°C with a CO_2 concentration increase of +180 ppm in Lusignan, France. Contrastingly, the models suggest that wheat is more resilient to heat stress and would require a temperature threshold equal to +3.6°C before experiencing yield losses below the baseline in Wageningen, the Netherlands (Fig. 4b). Based on the emulated projections seen in Fig. 4b, the models indicate that, should climate change be limited to a +3°C change and include a CO_2 concentration increase of +180 ppm, moderate temperature increases could, in fact, lead to gains in wheat production in this location.

Figure 4 also demonstrates the large variability between crop models and displays how this variability increases as a function of temperature. The differences between the first and third quartiles are much larger for higher temperature changes, at the given CO_2 concentration. This result indicates that the differences between crop models are much larger for high-temperature changes than for low-temperature changes. The level of divergence between the predictions of the crop models thus tends to increase with the temperature value considered in the climate change scenarios.

Increases in atmospheric CO_2 concentration

Figure 5 shows the effect of climate change at one site for both maize and wheat yields under increasing levels of CO_2 concentration, ranging from 0 to +360 ppm from the simulated baseline concentration (i.e., 360 to 720 ppm) at a constant temperature increase of +2°C. Figure 5a illustrates how all crop model simulations predict a positive effect on maize yields in Lusignan, France when exposed to increased CO_2 concentrations, but this effect is small and varies among crop models. The mean curve suggests that the effect of a temperature increase of +2°C is negative for the range of CO_2 concentration increases, thus the benefit of the increased CO_2 concentration does not outweigh the negative effect of the temperature increase. On average, the crop models predict a yield loss for maize, even at high CO_2 concentrations, due to this +2°C temperature change.

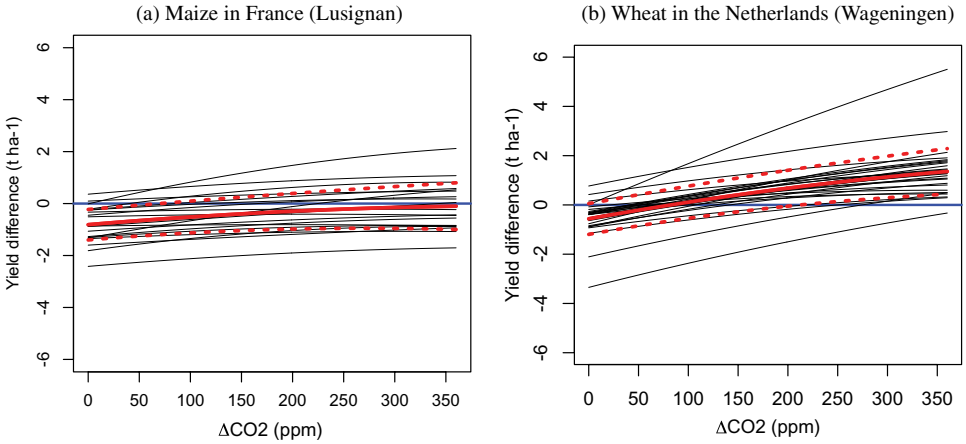


Fig. 5. The effect of climate change on yield for a temperature increase of +2°C, and for levels of CO_2 concentration increase ranging from 0 to +350 ppm. Results are reported for (a) maize and (b) wheat for one site per crop. Yield difference = yield obtained with a climate change scenario — yield obtained with the baseline (1981–2010). Each black curve corresponds to a given crop model. The black curves were obtained with the statistical model by using the crop model-specific coefficients α_{eki} (where $k = 0, \ldots, 6$ and $i = 1, \ldots, P$). The continuous red curve indicates the yield response as compared to the baseline scenario, i.e., the effect averaged over all crop models. The red dashed curves indicate the first and third quartiles of climate change effect computed over all crop models. The blue line indicates zero yield difference.

The fitted curves obtained for CO_2 response of wheat in Wageningen, the Netherlands are displayed in Figure 5b. Compared to maize, the effect of a CO_2 concentration increase is stronger for wheat. This effect is highly variable among crop models; some models demonstrate positive slopes over the range of CO_2 concentrations, whereas others show slopes close to zero. When averaged across all of the crop models, the effect of the +2°C temperature increase is positive (yield gain) as soon as the CO_2 concentration increase reaches 100 ppm.

Probabilistic thresholds

An important advantage of the meta-model is that it handles the interpolation between temperature levels and between CO_2 concentration levels. Our meta-model can thus be used to calculate temperature and [CO_2] thresholds that lead to yield loss or yield gain. Table 1 shows the thresholds of [CO_2] increase required to obtain a probability of maize and wheat yield gain higher than 0.5 (i.e., 50% chance of yield gain). These thresholds were computed for two values of temperature increase (+2 and +4°C) and four sites per crop. It would have been very difficult to compute them without a meta-model. Results show that, for wheat, climate change has 50% chance of resulting in a yield gain if [CO_2] increases by at least +117 ppm (depending on

Table 1. Levels of increased CO_2 concentration (ppm) required to obtain a probability of maize and wheat yield gain higher than 0.5 (i.e., 50% chance of yield gain). Concentrations were computed for two values of temperature increase (+2 and +4°C) and four sites per crop. Baseline scenario corresponds to $[CO_2] = 360$ ppm.

	Temperature change	
Site	+2°C	+4°C
Maize	**[CO_2]**	**[CO_2]**
Rio Verde, Brazil	> +360	> +360
Lusignan, France	> +360	> +360
Morogoro, Tanzania	> +360	> +360
Ames, USA	+269	> +360
Wheat	**[CO_2]**	**[CO_2]**
Balcarce, Argentina	+117	+358
Wongan Hills, Australia	0	+59
New Delhi, India	+112	+278
Wageningen, the Netherlands	+83	+222

the site) and if temperature concurrently increases by +2°C (Table 1). Required levels of $[CO_2]$ increases are much higher for maize (Table 1). Our meta-model has another advantage, although not fully illustrated here; it can be used to quantify the effects of temperature, $[CO_2]$, and precipitation on yields, their interactions, and their variability between the four considered sites and between all the considered crop models. It thus constitutes a powerful tool for exploring complex crop model responses to climate factors.

Conclusions

Our study shows that yield data simulated by an ensemble of complex dynamic-process crop models can be summarized by using statistical meta-models that are based on random coefficient regressions. These statistical models describe the between-crop model variability of the simulated yield data by using probability distributions. They can be used to compute key quantities such as mean yield loss, percentiles of yield loss, and probabilities of yield loss as functions of temperature change and CO_2 concentration change. These statistical meta-models can thus be helpful for analyzing the risk of yield loss due to climate change at the locations where the original simulations were conducted. The capabilities of the meta-models were illustrated by using two yield datasets generated by the

AgMIP pilot model intercomparison studies for maize and wheat. The results showed that:

- High CO_2 concentrations are likely to outweigh the negative effect of increasing temperature, leading to yield gains for wheat with climate change, but not for maize.
- Thresholds of temperature increase and CO_2 concentrations that lead to a specific risk level of maize and wheat yield loss can be computed by using the meta-model.
- The divergence between the maize and wheat crop models and therefore the uncertainty in the simulated results increases as a function of temperature (the higher the temperature change, the higher the between-crop model variability).

In the future, the proposed meta-model could be extended in two different ways. First, it could be applied to a dataset that includes simulations obtained for a higher number of sites. It will then be possible to include co-variables that describe site characteristics (e.g., soil type, agricultural practices) in the meta-model in order to explain the origin of the between-site variability. Second, our meta-model could be extended in order to describe the between-year variability of yields and to analyze the risk of extreme yield values for different climate scenarios. This could be achieved by including one or several additional random effects in the meta-model and by fitting this model to yearly yield data.

Acknowledgements

G. J. O'Leary was supported by the Victorian Department of Environment and Primary Industries and the Australian Grains Research and Development Corporation. P. Bertuzzi, J.-L. Durand, D. Makowski, P. Marte, D. Ripoche, and D. Wallach were partly supported by the INRA ACCAF meta-program. S. G. was supported by a grant from the Ministry of Science, Research and Arts of Baden-Württemberg (AZ Zu33-721.3-2) and the Helmholtz Centre for Environmental Research — UFZ, Leipzig.

References

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rotter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Muller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stockle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf,

J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A. R., Kersebaum, K. C., Kim, S.-H., Kumar, N. S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M. V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., and Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors?, *Global Change Biol.*, **20**(7), 2301–2320.

Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011). Climate trends and global crop production since 1980, *Science*, **333**, 616–620.

Pinheiro, J. C., and Bates, D. M. (2000). *Mixed-effects models in S and S-PLUS*, Springer, New York.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**,166–182.

Semenov, M. A., Wolf, J., Evans, L. G., Eckersten, H., and Iglesias, A. (1996). Comparison of wheat simulation models under climate change. 2. Application of climate change scenarios, *Clim. Res.*, **7**, 271–281.

Tubiello, F. and Ewert, F. (2002). Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change, *Eur. J. Agron.*, **18**, 57–74.

White, J. W., Hoogenboom, G., Kimball, B. A., and Wall, G. W. (2011). Methodologies for simulating impacts of climate change on crop production, *Field Crop Res.*, **124**, 357–368.

This page intentionally left blank

Chapter 12

Crop Diseases and Climate Change in the AgMIP Framework

Ariena H. C. van Bruggen[1], James W. Jones[1], Jose Mauricio C. Fernandes[2], Karen Garrett[3], and Kenneth J. Boote[1]

[1]*University of Florida, Gainesville, FL, USA*

[2]*EMBRAPA and Universidade de Passo Fundo, Passo Fundo, Brazil*

[3]*Kansas State University, Manhattan, KS, USA*

Introduction

The effects of global climate change on crop diseases cannot be fully understood without placing them in the context of other current global issues, such as human population growth, the resources needed to sustain this growth, urbanization, and environmental pollution. Concomitant with the population increase, the land area under food and fodder crops has increased and agricultural production has intensified with an increase in the use of fossil fuel, fertilizers, and pesticides, especially in emerging and developing countries (Mancini *et al*., 2005; Pretty and Hine, 2005).

The increasing human population uses more and more global non-renewable resources (such as oil, coal, and natural gas) for mobility as well as the production of food and industrial products. The burning of fossil fuel and other organic matter has led to an increase in CO_2 in the atmosphere, and there is strong evidence that the rising CO_2 concentrations are associated with a rise in global temperature (Fig. 1).

The average increase in global surface temperature is estimated to be at least 1.5–2.0°C between the end of the 20th century and the end of the 21st century (IPCC, 2014). It is expected that the number of extremely high temperature and rainfall events will increase, while the number of drought periods is also likely to

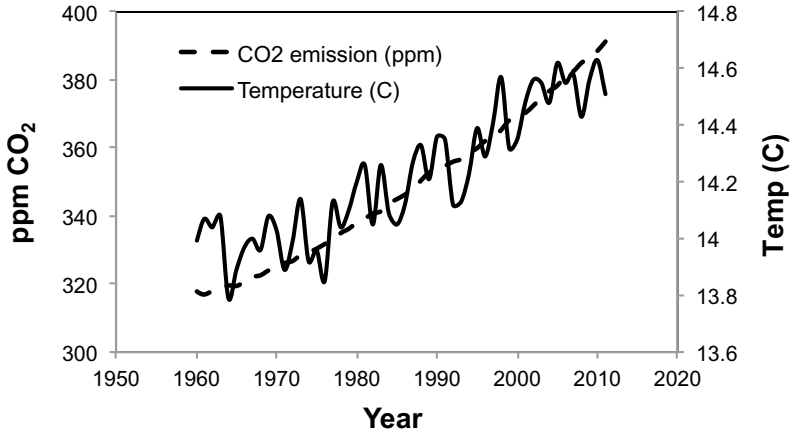


Fig. 1. Mean global temperature (°C) and CO_2 concentrations (ppm) in the atmosphere from 1960 to 2012. Redrawn from: Worldwatch Institute, 2013.

increase (IPCC, 2014). The changes in climate are not evenly distributed over the globe, and predictions are not very precise on small scales. Moreover, the seasonal and interannual, as well as the diurnal, predictions of temperatures and precipitation are still uncertain.

Changes in extreme events and daily oscillations in temperature and humidity could have significant effects on plant disease development. Global warming could also have profound effects on the distribution of species on earth. Crop species will probably be moved towards the poles and higher altitudes by humans, but wild species, especially K-strategists[1] like trees or some soil-inhabiting species, cannot move as fast as the expected change in climate (De Vries and Shade, 2013; Moe *et al*., 2013). Species that provide natural pest and disease control, which are often K-strategists, may trail behind the movement of crop species, increasing the risk of pest and disease outbreaks and yield insecurity (Radcliffe, 2013).

The expected changes in climate, crop production, and associated pests and diseases could have major impacts on food security, especially in developing countries when extreme weather events occur (Flood, 2010; Savary *et al*., 2012). In the last 50 years, grain production has grown steadily, but increases in food production have not been evenly distributed, and hunger is still rampant in many parts of the world (Wheeler and von Braun, 2013). To solve this problem, yield per hectare needs to improve, especially in countries with high population growth rates. However, in recent years, wheat (*Triticum vulgare* L. and *T. aestivum* L.) and rice (*Oryza sativa*

[1]K-strategists are organisms with a long-generation time and limited off-spring relative to the fast-growing and -multiplying r-strategists. Populations of K-strategists fluctuate near the carrying capacity of a stable ecosystem.

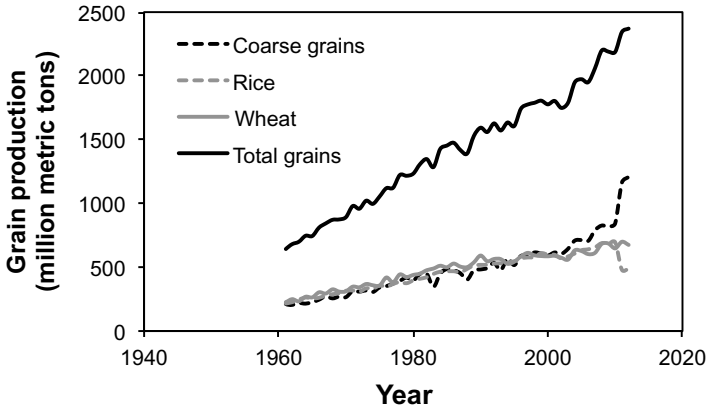


Fig. 2. Coarse grain (primarily maize), rice, wheat, and total grain production in the world from 1961–2012. Redrawn from Worldwatch Institute (2013).

L.) production per unit area have leveled off (Fig. 2) due to deterioration in soil fertility and continuing pest and disease pressure, despite the widespread application of fertilizers and pesticides (Lobell *et al*., 2009). Global crop losses are estimated to range between 20% to 40% due to diseases caused by fungi, bacteria, and viruses (Flood, 2010; Savary *et al*., 2012) and are estimated at 12% due to nematodes (Hassan *et al*., 2013), although accurate estimates are difficult to obtain. Crop losses have rarely been estimated or modeled in recent years, because research emphasis has shifted from applied field research and epidemiology to molecular host–pathogen interactions. Similarly, the effects of global climate change on disease epidemics and the associated crop losses have rarely been modeled (Savary *et al*., 2012).

Climate change will likely influence crop disease development in time and space through direct effects on the pathogen as well as indirect effects on the host. Thus far, researchers have mainly made broad statements about potential effects of climate change on plant diseases in many review papers (Garrett *et al*., 2006; Roos *et al*., 2011). For example, in northern countries a milder and more humid climate would stimulate the production of warmer-climate crops, and many pathogens and pests may survive increasingly in the winter season (Bebber *et al*., 2013; Harvell *et al*., 2002; Roos *et al.,* 2011). Several authors noted that effects of climate change on plant disease development have seldom been quantified using realistic plant disease models (Garrett *et al.*, 2006; Garrett *et al.*, 2013; Juroszek and von Tiedemann, 2013; Kaukoranta, 1996; Luck *et al.*, 2011; West *et al.*, 2012). The few models that predict effects of climate change on plant disease development have used average daily weather parameters (Bergot *et al*., 2004; Kaukoranta, 1996; Sparks *et al*., 2014; Stansbury and McKirdy, 2002). However, the effects of diurnal variation in temperature and relative humidity or leaf wetness on disease development may be at

least as important as daily averages (Garrett *et al.*, 2013; Scherm and van Bruggen, 1994; Shakya *et al.*, 2014), even though hourly values of these weather variables are difficult to predict (Scherm and van Bruggen, 1993b). Moreover, the relationships between biotic agents and their plant hosts are likely to be complex with multiple interactions and feedback loops (Garrett *et al.*, 2011).

Contrary to potential effects of climate change on plant diseases, potential effects on global crop production have been modeled extensively, primarily for cereal grains like wheat and rice, soybean (*Glycine max* L.), and potato (*Solanum tuberosum* L.) (Asseng *et al.*, 2013; Challinor *et al.*, 2013; Dube *et al*., 2013; Hijmans, 2003; Kiselev *et al.*, 2013; Nelson *et al.*, 2013; Rosenzweig and Parry, 1994; Rosenzweig *et al.*, 2013; Takle *et al.*, 2013; Tao and Zhang, 2013; Ye *et al.*, 2013). Recently, modeling teams have been formed through the Agricultural Model Intercomparison and Improvement Project (AgMIP) to compare different combinations of crop and economic models and understand their capabilities to assess climate change impact and adaptation strategies (Rosenzweig *et al.*, 2013a, 2013b). However, due to the large climate model errors in precipitation and temperature extremes on regional and local scales, the outcomes from crop models coupled with climate models are still uncertain with respect to the impact of climate change on agricultural productivity in specific areas (Ramirez-Villegas *et al.*, 2013).

For the same reasons, it is often difficult to model accurately the effects of climate change on plant pests and pathogens and their effects on crop productivity. These difficulties are compounded by the large range of temporal and spatial scales at which plant pests and pathogens operate, which ranges from hourly changes on individual plant parts to daily changes in plant populations and longer-term dynamics in plant communities (Plantegenest *et al.*, 2007; Skelsey *et al.*, 2010). Thus, there are currently only a few crop models that incorporate damage by insect pests and pathogens, according to a survey by the Consultative Group on International Agricultural Research (CGIAR) and Earth Systems Science Partnership (ESSP) among modelers (Rivington and Koo, 2010). None of the models used in the comparisons and assessments by AgMIP have yet considered the effects of pests and diseases on the management, yield, and economics of crop production under various climatological conditions.

Recently, a new interdisciplinary AgMIP team was formed to fill the gap in modeling efforts and take both crop growth and pest and disease development, plus the associated yield loss, into account. However, in this chapter we focus on plant diseases rather than pests. The AgMIP disease team will address the following questions: What are the most important diseases that are limiting food production globally, and what is the status of modeling and of models for those diseases and cropping systems? What approaches should be used to incorporate those models with crop

models for climate change studies? What is the current state of plant disease models relative to their potential use with crop and economic models for climate change impact and adaptation assessments? This chapter is the first effort of this AgMIP team to summarize the available literature to begin answering these questions.

The overall purpose of this chapter is to review the various approaches used to model plant diseases and their relevance to global change research, and to present approaches for simulating disease effects on future productivity, including methods for linking crop and disease models for climate change impact and adaptation assessments.

The specific objectives of this chapter are:

1. To assess the current state of disease models and their relation to global climate change.
2. To review the current state of crop models and their relation to pests and diseases.
3. To indicate potential linkages between crop and disease models in relation to global climate change.

The scope of this chapter is limited to globally important cropping systems and their main diseases. The emphasis is on high-impact diseases that occur over large areas as opposed to local or less significant epidemics (Birch *et al.*, 2012; Savary *et al.*, 2012; Shiferaw *et al.*, 2013). We first discuss the current status of plant disease modeling at different spatial and temporal scales, the modeling methods employed, the models that consider climate change and the expected movement of plant pathogens, as well as the modeled effects of crop management on disease development. Next we describe the current status of crop modeling approaches on different scales, the predicted effects of climate change on yield losses due to disease, as well as the effects of crop and disease management on projected crop productivity. We then consider the potential to link crop and disease models in various ways. The chapter ends with a discussion of approaches for incorporating disease models in the AgMIP integrated assessment frameworks at regional and global scales.

Disease Models

History of plant disease modeling

Plant disease models have been available since the 1960s when J. E. Vanderplank published his first mathematical models (Vanderplank, 1963). The first models were empirical in nature, describing relationships between a response variable and a predictor variable, often across time and less often across space. Later, analytical and numerical mechanistic models were developed based on the concept of a system, its components, and relationships between components or processes in determining

the behavior of the system. The first system models were focused on the pathogen or units of diseased tissue, while host growth was neglected or modeled simply as an empirical rate of increase in plant biomass (or susceptible tissue). Over time, disease models have become increasingly sophisticated, including host, pathogen and environment, as well as management effects. The process-based system models have scaled up from individual crops to mixed communities, ecosystems and landscapes. At the landscape level, geographic information systems (GIS) may be used (Aurambout *et al*., 2009; Wu *et al*., 2005). Recently, variability in space and time has been included, which enables probabilistic rather than deterministic model predictions (Gouache *et al*., 2013). Finally, a range of models, from simple to complex, have been used to predict and manage crop disease epidemics (Pavan *et al*., 2011; Rakotonindraina *et al*., 2012).

Modeling approaches in plant pathology

Waggoner (1977) gave an overview of the types of models available in 1977: "growth curves" for microbial multiplication, "physiological models" or simulation models that can incorporate effects of the environment on growth, and "geographic models" that take spatial distribution into account. This distinction is still relevant today, and more or less corresponds to the "analytical models", "compartmental models", and "mechanistic architectural models" described in Calonnec *et al.* (2013), although the geographical aspect is now much more refined with spatial aspects combined with physiological processes. We now distinguish between (1) mathematical empirical models, (2) analytical models, (3) mechanistic numerical-simulation models, (4) descriptive and analytical spatial and spatio-temporal models, (5) GIS-based mathematical empirical models, (6) network models, (7) functional–structural models, and (8) forecasting/management models. Initially, these models were all deterministic, but currently more and more stochastic elements are being included.

As plant pathogens operate at a wide range of scales, from microscopic to landscape, several modeling scales have been distinguished, both in space and over time. The temporal and spatial scales are connected: A model system on a small spatial scale is usually associated with a small time constant (minutes to hours), while processes occurring on a large regional or landscape scale can usually be modeled using a larger time step (days, months, or years), but there are exceptions. Historically, models for individual pathogens at the plant and crop scales were developed first, followed by larger-scale models more recently.

Most models in plant pathology have focused on individual pathogens, without considering plant growth and development directly. These individual pathogen models can be found among all different types of modeling approaches, except functional–structural models that combine the development of crop architecture with

physiological processes and sometimes with microclimate and disease (Casadebaig *et al*., 2012). For example, early deterministic and stochastic models were developed for fungal spore germination in relation to temperature (Eisensmith *et al.*, 1985; Waggoner and Parlange, 1974a, 1974b). Models for the growth and development of individual plants in the presence of individual pathogens often utilize mechanistic numerical-simulation or functional–structural approaches (Berger, 1976; Casadebaig *et al*., 2012; McCoy, 1976; Waggoner and Horsfall, 1969; Waggoner *et al.*, 1972).

Models that simulate plant populations and disease (mostly single diseases, rarely multiple diseases) are often mathematical, empirical, analytical, numerical-simulation, GIS-based, or network models (Chan and Jeger, 1994; Jeger *et al*., 2004; Stein *et al.*, 1994). If the populations of plants are field crops or orchards, disease development is most commonly described by temporal or spatio-temporal mechanistic simulation models or analytical models, and more recently by functional–structural crop models linked to disease models (Bruhn and Fry, 1981; Casadebaig *et al.,* 2012; Gilligan and van den Bosch, 2008; Robert *et al*., 2008; Singh *et al.*, 2013; van den Bosch *et al.* 1988; Zadoks and van den Bosch, 1994). Besides plants and pathogens, pathogen vectors may be included. In that case, the models are mostly analytical in nature (Chiyaka *et al*., 2012; Fargette *et al.*, 1994; Holt *et al.*, 1997; Jeger *et al.*, 2004; Madden *et al.*, 1990). At higher spatial scales, the regional and global spread of plant pathogens and disease may be simulated (Nutter *et al*., 2002). At higher complexity levels, whole farming systems with crop rotations and mosaics of crop species may be included (Leoni *et al.*, 2013).

Although plant pathogens are directly affected by the macroclimate for large-scale pathogen survival and by the microclimate around individual plants or inside a crop for infection, sporulation and spore release, climate factors are rarely included in host-pathogen models except for forecasting models, which are often empirical mathematical models (MacKenzie and Peres, 2012; Pavan *et al*., 2011). Climate factors, like temperature, relative humidity, and rainfall, can be taken into account more easily in numerical-simulation models than in analytical models, and the former may therefore be more useful in the context of predictions of global climate change effects on crop diseases and associated yield losses. However, in only a few cases, have plant disease models been connected to crop simulation models or crop loss models (Boote *et al.*, 1993; Del Ponte *et al.*, 2009; Panga *et al*., 2013; Singh *et al*., 2013).

Disease models that consider climate change

The number of disease models that address potential effects of climate change is still relatively small. Juroszek and von Tiedemann (2013) summarize the models that

have been used to study climate change and wheat diseases. Some empirical models have been formulated for the relationship between climate and disease epidemics, as well as climate analog models that use GIS or long-term disease datasets, and numerical-simulation models based on a systems analysis approach (Garrett *et al.*, 2006; Shaw, 2009). Until recently, the models suffered from several drawbacks, namely, lack of geographic detail in predicted climate and disease distribution, lack of accuracy in predicting daily (let alone hourly) and annual variation in weather patterns, lack of attention to changing CO_2 concentrations, and omission of the potential adaptation of the organisms involved (Garrett *et al.*, 2006; Ghini *et al.*, 2008; Scherm, 2004). However, recently, global climate models (GCMs) have significantly improved in both temporal and spatial scale, and shifts in the importance of particular diseases have been predicted (Ghini *et al.*, 2008; Juroszek and von Tiedemann, 2013; Shaw, 2009). These models for plant disease have been used to study the effects of predicted future average weather conditions, daily oscillations in weather variables, seasonal and interannual variability, and El Niño oscillations.

Models with a focus on average weather

Models that predict the risk of establishment of invasive, foliar pathogens in a new area are typically based on average climatic variables such as temperature, rainfall, and humidity (Er *et al.*, 2013; Scherm and van Bruggen, 1993a; Stansbury and McKirdy 2002). These are mostly empirical models that use indicators of combined weather parameters as input data. For example, an empirical model for potato late blight (*Phytophthora infestans* (Mont.) de Bary) is based on thermal time to predict the date of planting and emergence of potatoes, and thermal time on rainy days to predict the first late blight outbreak of the season. Results from this model indicate that an increase in the mean temperature in south Finland of 1°C will extend the period when chemical control for potato late blight is necessary by 10–20 days (Kaukoranta, 1996). In addition, a simulation model has been used to understand and assess potato late blight development in the Andes under climate change scenarios, including expected mean temperature and rainfall (Andrade-Piedra *et al*., 2005). Bergot *et al.* (2004) used a GCM scenario to predict the expansion of *Phytophthora cinnamomi* in oaks eastwards in Europe by modeling the temperature of the phloem in infected trees and evaluating overwintering probabilities of the pathogen. Thus, models based on average climate may predict the potential occurrence of a particular disease in a general region.

Models with diurnal changes in temperature and rainfall

Global climate change is not only associated with changes in average temperature and rainfall but also with differences in daily amplitudes and shifts in the frequency

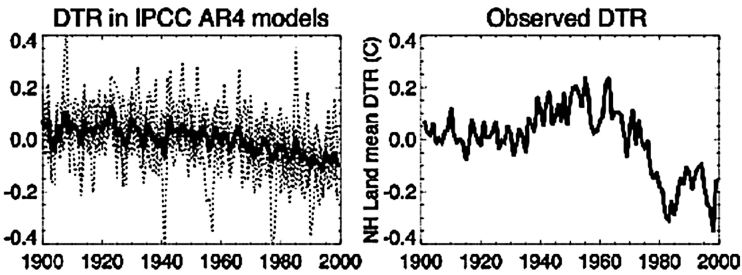


Fig. 3. Annual average diurnal temperature (°C) range (DTR) over land in the Northern Hemisphere (NH). Predicted by IPCC global climate models on the left, and observed data on the right (Wild, 2009).

of meteorological extremes (IPCC, 2014; Scherm 2004; Scherm and van Bruggen 1994). With climate change, the daily amplitudes of temperature may decrease, increase, or remain the same. In many areas, the daily minimum and maximum temperatures are both expected to increase; or the daily minimum may increase while the daily maximum temperature remains unchanged, which results in a decrease in temperature amplitude, the most common projection (Fig. 3).

In some other areas, like high-altitude regions, the daily maximum temperature may increase more than the daily minimum temperature if cloud cover is reduced, which increases the temperature amplitude. At increasing daily amplitudes, the relative growth rates of plant pathogens are expected to respond less drastically to an increase in average temperature than at smaller daily amplitudes due to non-linearity of the temperature optimum curve (Scherm and van Bruggen, 1994). However, at low average temperatures, e.g., at high altitudes, disease development is expected to increase at increasing diurnal temperature ranges (Shakya *et al*., 2014).

Models that simulate effects of climate change on plant disease have not considered diurnal oscillations in temperature, partly because these are not predicted well in global climate models (Sparks *et al*., 2014). The difference in temporal scale between climate models and pathogen response time makes it difficult to match the predicted climate scenarios with models of biological responses that require hourly or three-hourly input data (Scherm, 2004; Scherm and Bruggen, 1994). The spatial scale of plant pathogen responses to climate is also much finer than that predicted by climate models. Thus, application of the results from these models to disease development is very difficult (Scherm, 2004).

Models with seasonal or interannual changes in weather

Climate models predict that the number of extreme weather events, such as storms with heavy rainfall, will occur more frequently in the future (IPCC, 2014). These trends in more extreme weather and associated plant disease outbreaks have been

observed already. Hurricanes and tropical storms in 2004 and 2005 in Florida have been associated with long-range dissemination and an increase in local spread of citrus canker (Irey *et al.*, 2006). Wind speed and rainfall during hurricanes were used in a predictive model explaining the storm-related spread of citrus canker. The same hurricanes were also likely responsible for the introduction of Asian soybean rust (*Phakopsora pachyrhizi* Syd. and P. Syd.) in Florida. Based on low temperature and drought stresses incorporated in the CLIMEX model, it was predicted that soybean rust could be established year-round in Florida and Texas before it actually arrived there (Pivonia and Yang, 2004). The disease survives in those areas on kudzu plants (*Pueraria montana* (Lour.) Merr.), and rust spores are spread to neighboring soybean crops and further north annually. Escape from the canopy by wind was modeled analytically, and spore deposition was predicted accurately throughout the southeastern US (Andrade *et al*., 2009). In Brazil, final disease severity has been predicted from an empirical rainfall model, with temperature levels found to be less important than rainfall in terms of correlation (Del Ponte *et al.*, 2006). Thus, episodes of wind-driven rain are considered conducive for the regional spread of soybean rust and citrus canker.

Year-to-year and geographic variations in climate were used to develop an empirical weather-based model for *Phoma* stem canker epidemics on oilseed rape (*Brassica napus* L.). This model was combined with climate change predictions under different emission scenarios in different regions in the UK to predict severities of future epidemics (Evans *et al.* 2008). Future interannual variations in climate were not considered. Similarly, a disease model for *Septoria tritici* blotch on wheat was linked to predicted weather in France (Gouache *et al.*, 2013); besides average changes, the interannual variance and number of years particularly conducive for the disease were also considered. A Bayesian approach was used to account for uncertainty in climate, model parameters, and error. The effect of climate change varied depending on region, and there were large uncertainties associated with the predictions.

Scherm (2000) used fuzzy arithmetic to simulate the effects of uncertainty in a general pest model for climate change impact assessment. He compared the ecoclimatic index, a measure of the conduciveness of the weather for pest multiplication, for the present climate, a "crisp" change in climate (average predictions), and "fuzzy" climate change (triangular fuzzy numbers for the predicted extremes). Simulations with the crisp scenario resulted in minor changes in environmental favorability for a pest species compared with the control, while simulations with the fuzzy scenario resulted in changes in environmental favorability in some geographical regions. Thus, uncertainty in climate change projections must be reduced before reliable impact assessments can be achieved (Scherm, 2000).

Recently, Garrett *et al.* (2013) developed a model for cumulative yield loss as a function of an integrated weather conduciveness index for disease and used this

model to evaluate the effects of variation in conduciveness to cumulative yield loss. The greater the random variation in conduciveness (i.e., less autocorrelation), the larger the predicted yield loss. This kind of model could be used on different temporal scales.

Models with El Niño oscillations

The phenomenon of El Niño and La Niña oscillations that result in warming or cooling of the eastern tropical Pacific Ocean, respectively, and the associated changes in climate on agricultural regions in many parts of the world could possibly be affected by global warming (Fedorov and Philander, 2000). Both the frequency and amplitude of these oscillations could change. The influence of the El Niño Southern Oscillation (ENSO) is one of the best-characterized mechanisms of global variation in climate, and has been related to the development of rust diseases of wheat (Scherm and Yang, 1995). By using cross-spectral analysis, associations were found between the Southern Oscillation Index (SOI), a measure of ENSO strength, and wheat stripe rust (*Puccinia striiformis var. striiformis* Westend.) severity in North China and wheat stem rust (*Puccinia graminis* Pers.) severity in the US. The severity of stripe rust was associated with fluctuations in Northern Hemisphere teleconnection patterns at a periodicity of three years (Scherm and Yang, 1998). This association was probably due to the impact of the west Atlantic gulf stream pattern on winter temperatures.

Since global warming may alter the frequency and (or) intensity of ENSO events (Fedorov and Philander, 2000), a better understanding of the associations between disease and ENSO and other interannual climate cycles may lead to improved prediction of plant disease epidemics under climate change (Scherm and Yang, 1998). There are only relatively few models that describe the potential influence of expected climate change, including its variability in time and space, on plant disease epidemics, and practically no models that predict effects of climate change on yield losses due to diseases (Savary *et al.*, 2006; West *et al.*, 2012).

The need for such models was stressed in the report on the meta-analysis of crop modeling for climate change and food security survey (Rivington and Koo, 2010). It is important to realize that patterns of variance in predicted weather can have a major impact on disease development and potential yield loss (Garrett *et al.*, 2013). Creating such models for each individual disease-host combination is highly challenging, but models could be developed for a number of "ecotypes", i.e., pathogen-host combinations with similar ecological and epidemiological properties (West *et al.*, 2012). Models that take the variability changes as well as mean changes in predicted climate into account can lead to improved scenarios for projecting crop disease impacts and realistic decision support systems that contribute to developing and implementing adaptation strategies.

Disease models that address management effects

Disease management models have also progressed from smaller to large scales, namely from uniform single crops to mixed cropping systems, farming systems, and regions or landscapes. In the following paragraphs disease management models will be discussed at the various scales.

Disease management at the crop scale

Management strategies have often been considered distinct for diseases with multiple asexual infection cycles (polycyclic) and those with a single cycle per year (monocyclic). In the first case, reducing the initial inoculum or its efficacy is the most effective strategy, while for polycyclic diseases a reduction in the epidemic rate (for example by rate-reducing host resistance or spraying with fungicides) is considered most effective, although reduction of the initial inoculum should not be ignored (Madden *et al.*, 2007). Removal of inoculum has proven to be effective in practice and has been tested and compared with other management practices with the aid of analytical and numerical simulation models. For example, removal of symptomatic infectious flush (young, light green shoot) of a citrus tree infected by citrus greening, also called huanglongbing or yellow shoot disease, which is caused by an uncultured bacterium *Candidatus* Liberibacter spp., was predicted to have only marginal effect compared to removing the vectors (Asian citrus psyllids) by using insecticide sprays, although the effectiveness of these treatments was highly dependent on initiation time and frequency of application (Chiyaka *et al.*, 2012). Removal of infected plants when they just become infectious, sometimes without being symptomatic, could be effective (Chan and Jeger, 1994), but is difficult to accomplish.

Breeding programs to develop moderate host resistance based on multiple genes could reduce the epidemic rate, while strong host resistance based on one or few genes could lead to a delay in epidemic development until the single-gene resistance is "broken down" by an evolving pathogen. Deployment strategies of major single-resistance genes, such as by alternating their use or stacking genes, have been modeled to prevent or delay the emergence of resistance-breaking pathogens (Leonard, 1969; McDonald and Linde, 2002).

Besides host resistance, fungicides can be applied to slow down disease epidemics in crops. When the same fungicides are applied frequently, resistance in the pathogen population may build up. To prevent or slow down the development of fungicide resistance, fungicides can be alternated or used in mixtures (Kable and Jeffrey, 1980; Milgroom *et al.*, 1989).

The effects of these deployment strategies for host resistance (Birch and Shaw, 1997; García-Arenal and McDonald, 2003; Gilligan and van den Bosch, 2008; McDonald and Linde, 2002; van den Bosch and Gilligan, 2008) as well as fungicide applications (Kable and Jeffrey, 1980; Milgroom, 1990; Shaw, 2000) have been investigated by using various mathematical models. Models have also been used to investigate the direct effect of insecticide and fungicide applications on vector control and on disease development in order to design optimal disease management strategies that minimize economic and environmental costs and maximize crop returns (Castle and Gilligan *et al.*, 2012; Shtienberg *et al.*, 1989; van den Bosch and Gilligan, 2008).

In addition, many disease forecasting models, which are often based on past or predicted weather, have been developed and used (MacKenzie and Peres, 2012; Pavan *et al.*, 2011; Wu *et al.*, 2002, 2005). These models could potentially be utilized to predict effects of climate change on epidemic development of the diseases targeted, but their effects on crop yield are usually not included.

Disease management at the field scale: Mixed cropping or cultivar mixtures

Crop or cultivar mixtures and multiline cultivars have the potential to slow down or prevent epidemic development by plant pathogens (Chin and Wolfe, 1984; Cox *et al.*, 2004; Finckh and Mundt, 1992; Zhu *et al.*, 2000). The genotype unit area of a mixture could be a single plant, a patch of plants or a strip of plants (Finckh *et al.*, 2008). Effects of these management strategies have been supported by results from computer simulation modeling (Leonard, 1969; Mundt and Brophy, 1988; Mundt and Leonard, 1986; Skelsey *et al.*, 2010). For industrialized agriculture, the components of cultivar mixtures must possess phenotypic uniformity to allow mechanical harvesting operations (Mundt, 2002). However, morphological diversity in a cultivar mixture may be useful to alter canopy microclimate and crop susceptibility to disease (Finckh and Mundt, 1992; Zhu *et al.*, 2005).

The most common mechanisms that affect disease in mixtures are (1) dilution of inoculum due to the presence of resistant plants; (2) physical barriers to successful deposition created by resistant plants; (3) potential for induced host resistance when propagules are deposited on a neighboring plant for which they are avirulent; and (4) modification of the microclimate (Calonnec *et al.*, 1996; Garrett and Mundt, 1999; Mundt, 2002; Mundt and Browning, 1985; Zhu *et al.*, 2005). Overall yield of mixtures planted in a substitution design may be greater than the sum of the monocrops, although individual components of the mixture may yield less than the respective monocrops (Hiddink *et al.*, 2009). Generally speaking, within-field

diversity enhances the resilience not only towards pest and pathogen invasion, but also towards extreme weather events (Lin, 2011).

Disease management on the farming-system scale: Crop rotation and mosaics

Farming-system diversity that modifies the host distribution and frequency and/or the environment influences the incidence and severity of crop diseases. It can be achieved through planting and managing natural habitat interspersed in cropping areas, more extensive crop rotations, sod rotation, cover cropping, and reduced tillage. These practices may also affect vector populations and epidemic development. Crop rotation is the most common strategy used to manage soil-borne diseases. In practice, the management of crop diseases through crop choice, frequency, and sequence is complex as not only biological, but economic factors need to be taken into account (Ahmadi *et al.*, 2013; Kirkegaard *et al.*, 2008; Leoni *et al.*, 2013). Crop-rotation models and crop-sequencing models have been developed to design effective farm-management strategies, particularly to minimize soil-borne disease (Groot *et al.*, 2009; Lawes and Renton, 2010; Leoni *et al.*, 2013; van den Berg, 2006).

Dynamic linear and non-linear programming models have been developed to study the tradeoffs among land sustainability and crop productivity as affected by disease severity, and economic outcomes that result from different cropping decisions (Ahmadi *et al.*, 2013; Groot *et al.*, 2009). Such models support decisions on cropping sequences that maximize the net value of cropping per unit of land over a long-term time horizon. They could also be used to design mitigation strategies to minimize the impact of climate change. Similar to within-field diversity, crop and non-crop plant diversity on the farming-system scale is likely to enhance the resilience of the system towards pest and disease outbreaks as well as weather extremes (Lin, 2011). Thus, one adaptation approach for climate change is diversification of farming and cropping systems.

Disease management on the regional scale

Many foliar or vector-borne plant pathogens are dispersed over long distances (Madden *et al.*, 2007; Mundt *et al.*, 2009a) and can even spread on continental scales (Brown and Hovmøller, 2002), as exemplified by the recent expansion of soybean rust. Forecasting systems have been developed to predict long-distance transport from the movement of weather fronts, so that fungicide sprays can be initiated when inoculum is expected to arrive, for example, for soybean rust (Anonymous-a, 2014). The diseases caused by these pathogens may occur in patches of hosts, the so-called foci, which may expand as waves with a constant or accelerating radial speed (Mundt

et al., 2009b). They may also occur successively or simultaneously in different but interconnected regions; therefore, there is an increasing interest in the optimization of disease control at the landscape scale through the use of models (Rowthorn *et al.*, 2009; Skelsey *et al.*, 2010). Localized deployment of control methods around emerging foci (localized patches of disease) offers an alternative approach to area-wide control and minimizes costs (Forster and Gilligan, 2007; Gilligan *et al.*, 2007; Parnell *et al.*, 2010; Rowthorn *et al.*, 2009).

Local application of a control method like the use of a fungicide in one region benefits other regions by reducing the number of potential disease transfers between subpopulations and interconnected regions, thereby optimizing the deployment of control. This strategy has been supported by different epidemiological and economic modeling efforts that enabled determination of optimal control strategies in metapopulations at the landscape scale (Fabre *et al.*, 2012; Forster and Gilligan, 2007; Rowthorn *et al.*, 2009). Control strategies on the regional or landscape scale may be quite different from (but supplemental to) optimal strategies on the field scale (Parnell *et al.*, 2010). On the other hand, simultaneous treatments on a regional scale could be optimal for disease control both for the use of insecticides to control disease vectors (Anonymous-b, 2014) and the use of cultivar mixtures on a large scale (Zhu *et al.*, 2000). Regional diversity in terms of cropping patterns, including non-hosts for particular diseases may lead to a reduction in disease, especially if the susceptible host is planted on a smaller total acreage (Mundt *et al.*, 2011; Skelsey *et al.*, 2010). Regional diversity may also mitigate effects of climate change as crops and their associated diseases respond differently to changes in climate, in particular to extreme climate events (Garrett *et al.*, 2011; Luck *et al.*, 2011).

Crop Models

There are various modeling approaches to predict crop production and yield, ranging from empirical (regression methods as a function of temperature, rainfall, etc.) to functionally process-based and highly mechanistic approaches, including photosynthesis and respiration.

Regression techniques are used to estimate coefficients in linear or non-linear models in which crop yield is a function of independent variables such as temperature, rainfall, and other factors. Lobell *et al.* (2013) present examples of regression models that predict climatic effects on crop yield in various regions. In order to obtain the required coefficients, the regression approaches require large numbers of observed crop yield records along with historical weather for given sites or regions for the prior 20–30 years. The data may be aggregate yield statistics, such as county or district yields. To predict realistic effects of climate change, the

regressions may need to account for technology trends and genetic improvements over time, in addition to changes in temperature and other climate variables. Ancillary data such as government-supplied information on optimal sowing dates, harvest dates, N fertilization amounts, and soil-productivity indices may also be included in regression models.

Dynamic process-oriented crop models predict daily growth and yield for homogenous areas or points in the landscape. These models are site-specific, and thus need site-specific weather, soils, management, and cultivar-genetic information for the most accurate predictions, although the simulations can be aggregated up from multiple sites within a region to give district-level yield predictions. These models predict the daily accumulation of biomass and its partitioning into plant components (e.g., leaves, stems, and grain). Some dynamic crop models use simple functions to compute light interception, daily growth, and effects of the physical environment, including temperature, solar radiation, CO_2 and soil water, while others have more mechanistic detail regarding state variables and processes, such as photosynthesis and respiration. For example, the more mechanistic models consider leaf photosynthesis responses to light, temperature, and CO_2 at the level of rubisco kinetics and stomatal function with hourly time-steps, and consider tissue composition and synthesis/respiratory costs of growing new tissue (Boote *et al.*, 2013). The models may also differ considerably in how they predict crop transpiration, ranging from daily computations with standard evapotranspiration (ET) equations (e.g., Allen *et al.*, 1998), to more mechanistic hourly or more frequent solving of energy balance to predict ET and foliage temperature (Allen *et al.*, 2006).

Contrary to regression models, dynamic crop simulation models can account for new conditions such as future climate change and potential responses of farmers to these changes. Crop simulation models include functions that describe relationships of crop physiological processes to temperature, water availability, nitrogen nutrition, and day length. Those functions enable the models to respond to daily weather conditions in the past as well as in the future. In addition, the models accept inputs that describe management practices and genetic traits that may change over time, which again allows consideration of how adaptive management strategies or new genetic improvements may enhance production under current or future climate scenarios.

There are several different levels at which crop models predict growth and yield: Potential, attainable, or actual production. Potential production is predicted by the models as a function of site-specific weather (solar radiation, temperature, CO_2, and day length), but assuming no limitations from water deficit, lack of fertility, or pests/disease. Attainable production is that predicted when limitations from water and fertility are simulated. Actual production is what farmers achieve, and includes any and all limiting factors in the field, including the soil fertility and pest/disease aspects.

However, most crop models operate at the attainable yield level (considering water and N), and do not account for pest and disease effects, either mechanistically or *via* post-model processing. There are several reasons for the lack of attention for 4pests and diseases in crop models: (1) many crop models are relatively simple and not designed for linkage to pathogen or pest models; (2) similarly, models of pathogens or pests are often too simplistic to simulate their effects on crop physiology and yield; (3) the occurrence of pests and diseases often have a random component so that modeling the combined effects of the environment and pests and diseases on crop yield is not just a simple case of heat units and crop phenology driving pest and disease development; and (4) most crop models are parameterized for generally pest-free conditions in developed-country agriculture in which pest and disease effects are limited because optimal control practices are observed. Nevertheless, there have been some efforts in the past in which crop models have been used to link disease and crop models, and examples are summarized below.

Linking Crop and Disease or Pest Models

There are various ways in which pest damage and yield loss could be considered in descriptive regression models or mechanistic crop models.

Empirical approaches for predicting disease effects on yield

Regression methods have often been used for empirically modeling yield loss to diseases (Savary *et al.*, 2006). Empirical approaches to predicting yield losses often begin with equations (usually either Gompertz or logistic) that predict total disease or its components (e.g., defoliation and necrosis) over time, potentially with a rate parameter that is sensitive to temperature, rainfall, and relative humidity (Berger, 1981; Berger and Jones, 1985). Development of such an equation with semi-mechanistic rate parameters requires disease ratings, such as foliar percent necrosis, to be made under field conditions. In this approach, the total area under the disease progress curve (AUDPC) can be used as a proxy to estimate the relative yield loss. To be effective and to link this to yield, one would need to compare various AUDPC values to matching actual crop yields, to compute a yield-reduction coefficient or regression of yield against AUDPC as done by Singh *et al.* (2011a). This can be done to predict either relative or absolute yield reduction. The crop model could be used to predict the yield attainable from climate and fertility, with the relative pest disease reduction applied by post-processing of the yield loss AUDPC function.

Sharma-Poudyal and Chen (2011) used linear regression to fit wheat-yield loss to stripe rust as a function of temperature and rainfall in the Pacific Northwest of the US. Wheat-yield losses to this disease were best explained by winter temperatures

and rainfall. Regression methodology is generally good at hindcasting because historical data are used to train the models, but problems can be expected when these models are used to predict pest and disease outbreaks and associated yield losses under unknown conditions such as elevated CO_2 and temperature. Outbreaks and epidemics of pests and diseases are difficult to predict because they are not necessarily primarily weather-driven and thus are less predictable than temperature effects on crop development. For future crops, the CO_2 effect is relatively predictable and beneficial, although the future temperature effects are not as easy to model with regression equations because the future warmer climate is often not included in the data from which coefficients are derived.

Mechanistic simulation models of crop loss

For mechanistic process-based models, effects of pests and diseases on crop growth and yield are best addressed by considering the coupling points for the interactions as defined by Boote *et al.* (1983). These coupling points could be on processes like photosynthesis and transpiration, on state variables (mass, number, and area of organs), or on input resources. Boote *et al.* (1983) defined several types of disease or pest damage and examples of pathogens or pests in each category (Table 1). This categorization assists in identifying the appropriate coupling points in crop models, whether decreasing all state variables in the case of stand reducers such as the lesser cornstalk borer, or decreasing some state variables as in the case of tissue consumers such as foliar-feeding larvae, or reducing leaf photosynthesis as viruses do.

Assimilate sappers differ qualitatively from tissue consumers because they capture sugars and reduced nitrogen before those compounds are used to produce new structural crop tissue. Aphids, nematodes, and many fungi act to reduce photoassimilates available for crop growth prior to their use by plants for growth respiration and structure synthesis. Leaf senescence accelerators affect processes in the crop model that result in the loss of leaf carbon and nitrogen mass as well as leaf area (i.e., through multiple model state variables). While the outcome of this type of pest and disease damage is similar to that of tissue consumers, it may need to be modeled differently because the tissue simply senesces and falls off. Leaf-spot diseases display characteristics of several damage categories, namely photosynthesis rate reducer, assimilate sapper, as well as leaf senescence accelerator. Weeds are a good example of resource stealers, because they capture light (by shading the crop), capture water (by competing for soil water), and capture nutrients (by competing for nitrogen). Turgor reducers reduce water flow *via* roots and xylem. For example, the vascular wilt disease Verticillium wilt may reduce water transfer rate within the xylem.

Table 1. Damage categories: Crop pests and diseases, describing the damage they cause to crop model state variables, processes, secondary variables, and resource inputs, along with pest and pathogen examples (adapted from Boote *et al.*, 1983).

Damage categories	State variables affected	Process affected	Secondary variables affected	Resource inputs	Examples
Stand reducers	All plant organs				Lesser cornstalk borer, seedling damping-off
Photosynthesis rate reducers		Photosynthesis, C-input			Leaf spot, virus
Leaf senescence accelera-tors		Leaf senes-cence/ abscission	Leaf mass and area		Leaf spot
Resource stealers				Capture light, nutrients, water	Weeds, some pathogens
Assimilate sappers	Phloem sap (assimilate)				Aphids, nematodes Diseases
Tissue consumers	Leaf, stem, root, pod, grain				Fall armyworm Necrotrophic pathogen
Turgor reducers		Water flow			Verticillium wilt

Linking disease progress models to crop models

This linking approach refers to the simulation of dynamic disease models followed by the incorporation of the disease progress from the disease model into a crop model. This is the approach used in the Decision Support System for Agrotechnology Transfer (DSSAT) crop models (e.g., Batchelor *et al.*, 1993; Boote *et al.*, 1993; Jones *et al.*, 2003). For example, the coupling point approach for pest damage was incorporated into DSSAT soybean model SOYGRO and the peanut (*Arachis hypogaea* L.) model PNUTGRO in the early 1990s by Batchelor *et al.* (1993), based on data from Bourgeois *et al.* (1991). They developed a disease input routine for the DSSAT system that reads the field-observed pest and disease damage from a file. The model program converts the damage into the correct units and interpolates it for the appropriate times during simulation. The damage is then connected to the photosynthesis processes (to reduce the rate), senescence processes (to abscise leaves),

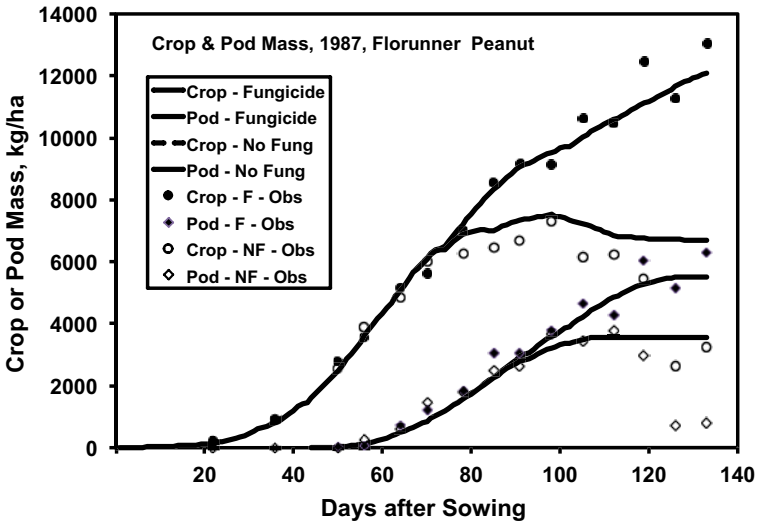


Fig. 4. Simulated and observed total biomass and pod mass of Florunner peanut in 1987 at Gainesville, FL, with and without fungicide for leaf-spot control (simulated with data from Bourgeois *et al.*, 1991).

or the model state variable integration routine (in which pest-damaged tissue is subtracted from existing tissues or assimilate is removed from the photo-assimilate available for growth). In these models disease progress affects both photosynthesis and defoliation, with the crop model simulating consequences for yield loss. Recently, the CSM-CROPGRO-peanut model was coupled to a late leaf-spot (*Cercospora arachidicola*) routine by Singh *et al.* (2011b). The leaf photosynthesis function was adjusted for leaf-spot disease severity based on measured photosynthesis of single leaves against observed percentage of necrosis. The coupled model accurately predicts leaf assimilation, canopy assimilation, and growth dynamics of peanut affected by leaf-spot disease (Singh *et al.*, 2013). Figure 4 shows the simulated total biomass and pod mass for Florunner peanut with fungicide treatment compared to no fungicide treatment for 1987 (Bourgeois *et al.*, 1991), for which scouting data on percentage defoliation and percentage necrosis were entered into the CSM-CROPGRO-peanut model. Figure 5 shows that mid-day canopy assimilation over time was accurately predicted for both treatments of Bourgeois and Boote (1992) as well, by following this approach.

The pest coupling approach allows the pest and disease effects on final yield of the crop to be an outcome of how the pest-damage coupling affects the in-season crop state variables such as leaf area index (LAI) and processes such as photosynthesis, through to the integrated balance of carbon and nitrogen available for growth and yield. For example, foliar-feeding insect damage reduces LAI, and the simulation

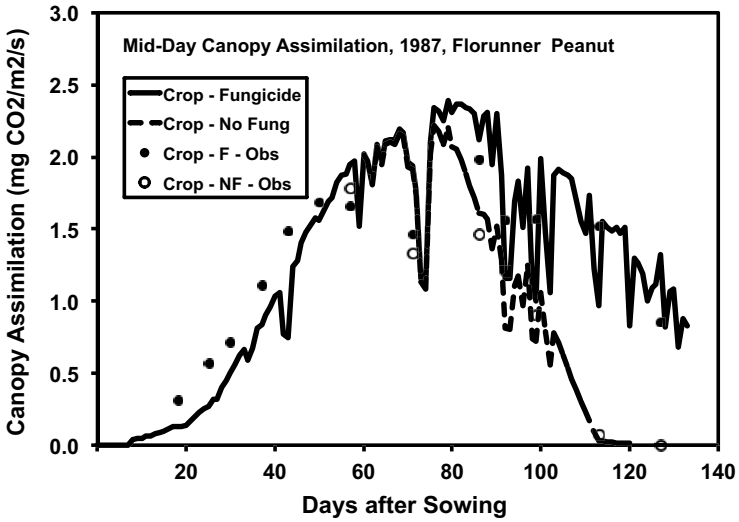


Fig. 5. Simulated and observed mid-day canopy assimilation of Florunner peanut in 1987 at Gainesville, FL, with and without fungicide for leaf-spot control (simulated with data from Bourgeois and Boote, 1992).

with lower LAI will predict less photosynthesis, less dry matter accumulation, and lower yield. Moreover, the effect of leaf-spot damage on final yield is not a result of an arbitrary reduction, but is obtained through the abscission of leaves (which thus reduces LAI), which in turn reduces canopy photosynthesis, along with direct leaf-spot effects on the light-saturated leaf photosynthesis rate, which also affects canopy photosynthesis. The simulation continues to integrate the reduction in accumulated photosynthesis and subsequent partitioning to pod and grain yield that results in lower yield.

The pest coupling method has an advantage over empirical disease and crop loss prediction because a crop model fully considers the effects of current weather and management factors on simulated growth and yield processes, such that yield loss from a given disease or pest will not be a static fraction but will take into account climatic and management factors that affect the climatically attainable crop yield. For example, if pest damage dramatically reduces LAI, then the crop demand for water will be less and drought effects could be less severe. Pest coupling in this manner also allows consideration of future climate change effects, because the dynamic crop models simulate increased crop photosynthesis and reduced transpiration associated with elevated CO_2.

This coupling approach works well if scouting data on pest and disease damage are available. However, this feature is also a disadvantage as the assessment is limited to being a post analysis of pest effects. The real need is a combined crop and disease

modeling system for future climate conditions that does not rely on pest scouting data. Pests and diseases must be predicted in either a stand-alone mode or in a parallel pest or disease model that responds to weather and creates damage effects that can be coupled to the crop model in a daily simulation time-step, either *via* prior pest simulation or parallel dynamic concurrent coupling to the crop model.

Directly coupled disease and crop models

Direct coupling of disease and crop models is rare, but has been done for several crops. For example, Del Ponte *et al.* (2009) developed a dynamic model of leaf rust for wheat (*Puccinia triticina* Erikss.) in Brazil, which takes into account daily progress of infection, dispersal of asexual spores (urediniospores), germination, and disease development on plant leaves as affected by weather and crop conditions. They coupled this leaf-rust model to the DSSAT-CERES-CROPSIM wheat model and have been using the coupled model to estimate the economic consequences of leaf rust and implications of introducing a partial-resistance gene into the wheat varieties that are grown in Brazil. Another example is the incorporation of a soybean rust disease model into the DSSAT-CROPGRO-Soybean model for studying the impacts of this disease on soybean production in Brazil (Rodrigues *et al.*, 2013). This approach is practical for high-impact diseases that are widespread around the world.

In addition to the physiological crop simulation models, disease models have also been coupled to the recently developed functional–structural models. In these models, the structural part consists of a crop architecture development model, while the functional part consists of a mechanistic crop physiological model. Functional–structural models are driven by climatic factors, which could be specified at the microclimate level. Such microclimate-functional–structural models are very suitable for the simulation of aerial diseases in space and time (Casadebaig *et al*., 2012; Robert *et al*., 2008). However, they may require too much computing time to be scaled up for the prediction of climate change effects.

Integrating Disease Models into the AgMIP Framework

This review indicates that there is a strong need to integrate pest and disease models into the AgMIP framework for integrated assessments of the effects of climate change on crop productivity. In some production systems, agricultural producers make use of resistant varieties and chemicals to control diseases such that actual production may be near to the attainable yield levels that are determined by water and nutrient availability. However, even in these systems, the costs of production depend on the methods used to control diseases and thus economics are affected even

though yields may not be affected very much. In addition, resistance to insecticides, fungicides, and bactericides is increasing so that some diseases can no longer be controlled effectively (e.g., Hewitt, 1998). This holds especially for some viral diseases transmitted by whiteflies (e.g., *Bemisia* spp.) and leaf-spot diseases caused by bacteria (e.g., *Xanthomonas* spp.) that are resistant to copper fungicides (Behlau *et al.*, 2011; Navas-Castillo *et al.*, 2011). Furthermore, in many production situations, particularly in developing countries, knowledge about diseases and their management may be limited or disease-resistant crops and fungicides may not be available so that crop losses tend to be high (Mancini *et al.*, 2007, 2008). Compounding this problem is the fact that climate change may have a major influence on the complex of pests and diseases and the magnitude of their damage in many agricultural regions (Anderson *et al.*, 2004; IPCC, 2014; Garrett, 2008; Rosenzweig *et al.*, 2001). Thus, integrated crop, pest, and disease management with appropriate cultural practices, crop varieties, and chemicals will be needed to control plant pathogens and their vectors as the damage to crops without adequate control is likely to change through time under a changing climate.

AgMIP climate change assessments currently operate on two scales: Global/national and regional/field. Both make use of crop models to estimate the effects of climate change on crop yields. Although these analyses are increasingly including livestock systems that are also affected by pests and diseases, we limited this chapter to cropping systems. The regional integrated assessment protocols make use of crop models to simulate crop production on the field scale for individual households by using current and future climate conditions and by using current production systems as well as systems aimed at adapting to climate change. Figure 5 shows a flow chart of the components of that integrated assessment with a central box that shows crop and livestock models. However, in the current implementation of the framework, effects of pests and diseases on production and costs of production are ignored.

In this chapter, we describe three approaches to link crop and disease models. In the first approach, disease losses are estimated by using empirical relationships between disease progress and crop yield; this requires that disease progress is first modeled, then the crop model is used to estimate yields without damage, followed by the use of the empirical relationship to reduce yield for each field. In this case, disease and crop models are simulated separately. The second approach couples disease progress simulations during the season with dynamic crop models so that the timing and magnitude of disease progress is simulated simultaneously with the effects of climate and management on crop growth and yield. This is the approach used by the "coupling point" method implemented in the DSSAT models (Batchelor *et al.*, 1993; Boote *et al.*, 1993; Jones *et al.*, 2003). In this case, either the disease model is simulated prior to the crop model or field scouting damage is obtained,

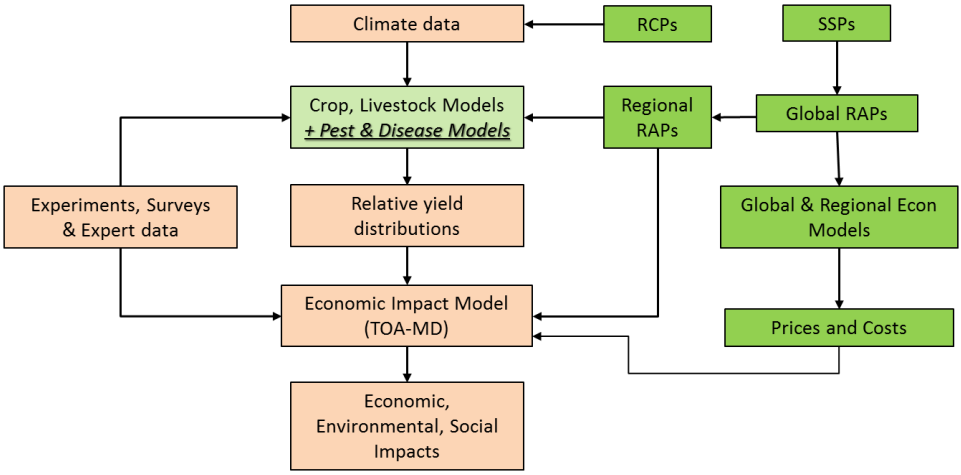


Fig. 6. Schematic of the AgMIP regional integrated assessment protocols used to simulate climate change impacts and adaptation at the household level. Note that the box that shows crop and livestock models was modified for this figure to show where the pest and disease models need to be linked with crop and livestock models (modified from AgMIP, 2013). (RCP — representative concentration pathway; SSP — shared socioeconomic pathway; and RAP — representative agricultural pathway.)

then the time course of disease damage is fed into the crop models. A third approach involves the coupling of crop and disease models so that the simulation of each component is dependent on the other as time progresses. Good examples of the third approach are the models by Del Ponte *et al.* (2009) and Rodrigues *et al.* (2013).

The influence of the diseases on crop yield can be estimated by using any of the three approaches. However, the empirical approach may be less desirable than the other two because it is not likely that an empirical function developed in one environment will be robust for use across other production environments through time as climate change proceeds. This is especially the case because disease development is highly dependent on weather conditions and the physiology of the host plants.

Pest and disease development, as well as nutrient availability and crop growth, are affected by previous crops and cropping activities in the rotation (Dogliotti Moro *et al.*, 2013; Leoni *et al.*, 2013). Thus, crop rotations would also need to be included in models meant to predict effects of climate change on crop productivity on a regional scale.

The second scale on which AgMIP performs its integrated assessments is the national-to-global scale (Rosenzweig *et al.*, 2013). In this case, weather, soil, and management inputs are provided at grid points on a global basis. Here again, there are no pest and disease models currently in use for these gridded crop simulation studies. As in the regional case, disease models would need to be developed by using climate and management information and then the disease outcome at each grid cell

would be used either as input to the crop models or to functions that would estimate yield loss.

Since most crop models do not currently have the capability to respond to the coupling points, there is a choice between using only these crop models that have coupling point capability or using multiple crop models along with the empirical yield-reduction approach. However, we recommend that crop models at both regional and global scales should be modified to include inputs of pest and disease damage in ways similar to the coupling point approach shown in Table 1.

References

AgMIP (2013). *Guidelines for Regional Integrated Assessments: Handbook of Methods and Procedures*. Available at: http://www.agmip.org/wp-content/uploads/2013/10/AgMIP-Regional-Integrated-Assessment-Handbook-v5.pdf. Accessed on 24 September 2014.

Ahmadi, B. V., Burnett, F. J., Young, C. S., McQuilken, M. P., and Stott, A. W. (2013). *Reducing the impact of sclerotinia disease by determining optimum crop rotations using dynamic programming*, 87th Annual Conference of the Agricultural Economics Society, University of Warwick, United Kingdom, 8–10th April 2013. Available at: http://purl.umn.edu/152213. Accessed on 24 September 2014.

Allen, R. G., Pereira, L. S., Raes, D., and Smith, M. (1998). *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*, United Nations Food and Agriculture Organization, Irrigation and Drainage Paper 56, United Nations, Rome, Italy, p. 300.

Allen, R. G., Pruitt, W. O., Wright, J. L., Howell, T. A., Ventura, F., Snyder, R., Itenfisu, D., Steduto, P., Berengena, J., Yrisarry, J. B., Smith, M., Pereira, L. S., Raes, D., Perrier, A., Alves, I., Walter, I., and Elliott, R. (2006). A recommendation on standardized surface resistance for hourly calculation of reference ETo by the FAO56 Penman-Monteith method, *Agric. Water Manage.*, **81**, 1–22.

Anderson, P. K., Cunningham, A. A., Patel, N. G., Morales, F. J., Epstein, P. R., and Daszak, P. (2004). Emerging infectious diseases of plants: Pathogen pollution, climate change and agrotechnology drivers, *Trends in Ecol. Evol.*, **19**, 535–544.

Andrade, D., Pan, Z., Dannevik, W., and Zidek, J. (2009). Modeling soybean rust spore escape from infected canopies: Model description and preliminary results, *J. Appl. Meteorol. Climatol.*, **48**, 789–803.

Andrade-Piedra, J. L., Hijmans, R. J., Forbes, G. A., Fry, W. E., and Nelson, R. J. (2005). Simulation of potato late blight in the Andes. I: Modification and parameterization of the LATEBLIGHT model, *Phytopathology*, **95**, 1191–1199.

Anonymous-a (2014). *Integrated Pest Management — Pest Information Platform for Extension and Education*. Available at: http://sbr.ipmpipe.org/cgi-bin/sbr/public.cgi. Accessed on September 24 2014.

Anonymous-b (2014). *Citrus Health Management Areas (CHMAs)*. Available at: http://www.crec.ifas.ufl.edu/extension/chmas/chma_overview.shtml. Accessed on September 24 2014.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck,

T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Aurambout, J. P., Finlay, K. J., Luck, J., and Beattie, G. A. C. (2009). A concept model to estimate the potential distribution of the Asiatic citrus psyllid (*Diaphorina citri* Kuwayama) in Australia under climate change — A means for assessing biosecurity risk, *Ecol. Modelling*, **220**, 2512–2524.

Batchelor, W. D., Jones, J. W., Boote, K. J., and Pinnschmidt, H. O. (1993). Extending the use of crop models to study pest damage, *Trans. ASAE*, **36**, 551–558.

Bebber, D. P., Ramotowski, M. A. T., and Gurr, S. J. (2013). Crop pests and pathogens move polewards in a warming world, *Nat. Clim. Change*, **3**, 985–988.

Behlau, F., Canteros, B. I., Minsavage, G. V., Jones, J. B., and Graham, J. H. (2011). Molecular characterization of copper resistance genes from *Xanthomonas citri* subsp. *citri* and *Xanthomonas alfalfa* subsp. *Citrumelonis.*, *Appl. Environ. Microbiol.,* **77**, 4089–4096.

Berger, R. D. (1976). Computer simulation of *Cercospora apii* and *Helminthosporium turcicum*, *Proc. Am. Phytopathol. Soc.*, **3**, 217.

Berger, R. D. (1981). Comparison of the Gompertz and logistic equations to describe plant disease progress, *Phytopathology*, **71**, 716–719.

Berger, R. D. and Jones, J. W. (1985). A general model for disease progress during changing host growth with functions for variable latency and lesion growth, *Phytopathology*, **75**, 792–797.

Bergot, M., Cloppet, E., Pérarnaud, V., Déque, M., Marcais, B., and Desprez-Loustau, M. L. (2004). Simulation of potential range expansion of oak disease caused by *Phytophthora cinnamomi* under climate change, *Global Change Biol.*, **10**, 1539–52.

Birch, P. R., Bryan, G., Fenton, B., Gilroy, E. M., Hein, I., Jones, J. T., Prashar, A., Taylot, M. A., Torrance, L., and Toth, I. K. (2012). Crops that feed the world 8: Potato: Are the trends of increased global production sustainable?, *Food Security*, **4**, 477–508.

Birch, C. P. D. and Shaw, M. W. (1997). When can reduced doses and pesticide mixtures delay the build-up of pesticide resistance? A mathematical model, *J. Appl. Ecol.*, **34**, 1032–1042.

Boote, K. J., Batchelor, W. D., Jones, J. W., Pinnschmidt, H., and Bourgeois, G. (1993). "Pest damage relations at the field level", in Penning de Vries, F. W. T., Teng, P., and Metselaar, K. (eds.), *Systems Approaches for Agricultural Development*, Kluwer Academic Publishers, Dordrecht, the Netherlands, pp. 277–296.

Boote, K. J., Jones, J. W., Mishoe, J. W., and Berger, R. D. (1983). Coupling pests to crop growth simulators to predict yield reductions, *Phytopathology*, **73**, 1581–1587.

Boote, K. J., Jones, J. W., White, J. W., Asseng, S., and Lizaso, J. I. (2013). Putting mechanisms into crop production models, *Plant Cell Environ.*, **36**, 1658–1672.

Bourgeois, G. and Boote, K. J. (1992). Leaflet and canopy photosynthesis of peanut affected by late leaf spot, *Agron. J.*, **84**, 359–366.

Bourgeois, G., Boote, K. J., and Berger, R. D. (1991). Growth, development, yield, and seed quality of Florunner peanut affected by late leaf spot, *Peanut Sci.*, **18**, 137–143.

Brown, J. K. M. and Hovmøller, M. S. (2002). Aerial dispersal of pathogens on the global and continental scales and its impact on plant disease, *Science*, **297**, 537–541.

Bruhn and Fry (1981). Analysis of potato late blight epidemiology by simulation modeling, *Phytopathology*, **71**, 612–616.

Calonnec, A., Burie, J.-B., Langlais, M., Guyader, S., Saint-Jean, S., Sache, I., and Tivoli, B. (2013). Impacts of plant growth and architecture on pathogen processes and their consequences for epidemic behavior, *Eur. J. Plant Pathol.*, **135**, 479-497.

Calonnec, A., Goyeau, H., and de Vallavieille-Pope, C. (1996). Effects of induced resistance on infection efficiency and sporulation of *Puccinia striiformis* on seedlings in varietal mixtures and on field epidemics in pure stands, *Eur. J. Plant Pathol.*, **5**, 733–41.

Casadebaig, P., Quesnel, G., Langlais, M., and Faivre, R. (2012). A generic model to simulate airborne diseases as a function of crop architecture. *PLos ONE*, **7**, e49406.

Castle, M. D. and Gilligan, C. A. (2012). An epidemiological framework for modeling fungicide dynamics and control, *PLoS One*, **8**, e40941.

Challinor, A. J., Smith, M. S., and Thornton, P. (2013). Use of agro-climate ensembles for quantifying uncertainty and informing adaptation, *Agric. Forest Meteorol.*, **170**, 2–7.

Chan, M. S. and Jeger, M. J. (1994). An analytical model of plant virus disease dynamics with rogueing and replanting, *J. Appl. Ecol.*, **31**, 413–427.

Chin, K. M. and Wolfe, M. S. (1984). The spread of *Erysiphe graminis* f. sp. *hordei* in mixtures of barley varieties, *Plant Pathol.*, **33**, 89–100.

Chiyaka, C., Singer, B. H., Halbert, S. E., Morris, J. G., and van Bruggen, A. H. C. (2012). Modeling huanglongbing transmission within a citrus tree, *Proc. Nat. Acad. Sci.,* **109**, 12213–12218.

Cox C. M., Garret, K. A., Bowden, R. L., Fritz, A. K., Dendy, S. P., and Heer, W. F. (2004). Cultivar mixtures for the simultaneous management of multiple diseases: Tan spot and leaf rust of wheat, *Phytopathology*, **94**, 961–969.

Del Ponte, E. M., Godoy, C. V., Li, X., and Yang, X. B. (2006). Predicting severity of Asian soybean rust epidemics with empirical rainfall models, *Phytopathology*, **96**, 797–803.

Del Ponte, E. M., Fernandez, J. M. C., Pavan, W., and Baethgen, W. (2009). A model-based assessment of the impacts of climate variability on Fusarium head blight seasonal risk in southern Brazil, *J. Phytopathol.*, **157**, 675–681.

De Vries, F. T. and Shade, A. (2013). Controls on soil microbial community stability under climate change, *Front. Microbiol.*, September.

Dogliotti Moro, S., García, M. C., Peluffo, S., Dieste, J. P., Pedemonte, A. J., Bacigalupe, G. F., Scarlato, M., Alliaume, F., Alvarez, J., Chiappe, M., and Rossing, W. A. H. (2014). Co-innovation of family farm systems: A systems approach to sustainable agriculture, *Agric. Systems,* **126**, 76–86.

Dube, S., Scholes, R. J., Nelson, G. C., Mason-D'Croz, D., and Palazzo, A. (2013). South African food security and climate change: Agriculture futures, *Economics*, 2013–2035. Available at: http://www.economics-ejournal.org/economics/discussionpapers/2013-35. Accessed on 24 September 2014.

Eisensmith, S. P., Rabbinge, R., and Zadoks, J. C. (1985). Development of stochastic spore germination model, *Neth. J. Plant Pathol.*, **91**, 137–150.

Er, H. L., Roberts, P. D., Marois, J. J., and van Bruggen, A. H. C. (2013). Potential distribution of citrus black spot in the United States based on climatic conditions, *Eur. J. Plant Pathol.*,**137**, 635–647.

Evans, N., Baierl, A., Semenov, M. A., Gladders, P., and Fitt, B. D. L. (2008). Range and severity of a plant disease increased by global warming, *J. Roy. Soc. Interface*, **5**, 525–531.

Fabre, F., Rousseau, E., Mailleret, L., and Moury, B. (2012). Durable strategies to deploy plant resistance in agriculture landscapes, *New Phytol.*, **193**, 1064–1075.

Fargette, D., Jeger, M. J., Fauquet, C., and Fishpool, L. D. C. (1994). Analysis of temporal disease progress of African cassava mosaic virus, *Phytopathology***, 84**, 91–98.

Fedorov, A. V. and Philander, S. G. (2000). Is El Niño changing?, *Science*, **288**, 1997–2002.

Finckh, M. R., Hayer, F., Schulte-Geldermann, E., and Bruns, C. (2008). Diversität, Pflanzenernährung und Prognose: Ein integriertes Konzept zum Management der Kraut- und Knollenfäule in der Ökologischen Landwirtschaft, *Gesunde Pflanzen*, **60**, 159–170.

Finckh, M. R. and Mundt, C. C. (1992). Plant competition and disease in genetically diverse wheat populations, *Oecologia*, **91**, 81–92

Flood, J. (2010). The importance of plant health to food security, *Food Security*, **2**, 215–231.

Forster, G. and Gilligan, C. A. (2007). Optimizing the control of disease infestations at the landscape scale, *Proc. Natl. Acad. Sci. USA,* **104**, 4984–4989.

García-Arenal, F. and McDonald, B. A. (2003). An analysis of the durability of resistance to plant viruses, *Phytopathology*, **93**, 941–952.

Garrett, K. A. (2008). "Climate change and plant disease risk", in *Global Climate Change and Extreme Weather Events: Understanding the Potential Contributions to the Emergence, Reemergence and Spread of Infectious Disease*, National Academy of Science, Institute of Medicine, Washington D. C., 143–155.

Garrett, K. A., Dendy, S. P., Frank, E. E., Rouse, M. N., and Travers, S. E. (2006). Climate change effects on plant disease: Genomes to ecosystems, *Ann. Rev. Phytopathol.,* **44**, 489–509.

Garrett, K. A., Dobson, A. D. M., Kroschel, J., Natarajan, B., Orlandini, S., Tonnang, H. E. Z., and Valdivia, C. (2013). The effects of climate variability and the color of weather time series on agricultural diseases and pests, and on decisions for their management, *Agric. Forest Meteorol.*, **170**, 216–227.

Garrett, K. A., Forbes, G. A, Savary, S., Skelsey, P., Sparks, A. H., Valdivia, C., van Bruggen, A. H. C., Willocquet, L., Djurle, A., Duveiller, E., Eckersten, H., Pande. S., Vera Cruz, C., and Yuen, J. (2011). Complexity in climate change impacts: A framework for analysis of effects mediated by plant disease, *Plant Pathol.*, **60**, 15–30.

Garrett, K. A. and Mundt, C. C. (1999). Epidemiology in mixed host populations, *Phytopathology*, **89**, 984–990.

Ghini, R., Hamada, E., and Bettiol, W. (2008). Climate change and plant diseases, *Sci. Agric.*, **65**, 98–107.

Gilligan, C. A. and van den Bosch, F. (2008). Epidemiological models for invasion and persistence of pathogens, *Annu. Rev. Phytopathol.*, **46**, 385–418.

Gilligan, C. A., Truscott, J. E., and Stacey, A. J. (2007). Impact of scale on the effectiveness of disease control strategies for epidemics with cryptic infection in a dynamical landscape: An example for a crop disease, *J. Roy. Soc. Interface*, **4**, 925–934.

Gottwald, T. R., da Graça, J., and Bassanezi, R. (2007). Citrus canker and citrus huanglongbing, two exotic bacterial diseases threatening the citrus industries of the western hemisphere, *Outlooks on Pest Management*.

Gouache, D., Bensadoun, A., Brun, F., Page, C., Makowski, D., and Wallach, D. (2013). Modeling climate change impact on *Septoria tritici* blotch (STB) in France: Accounting for climate model and disease model uncertainty, *Agric. Forest Meteorol.*, **170**, 242–252.

Groot, J. C. J., Rossing, W. A. H., Tichit, M., Turpin, N., Jellema, A., Baudry, J., Verburg, P. H., Doyen, L., and van de Ven, G. W. J. (2009). On the contribution of modeling to multifunctional agriculture: Learning from comparisons, *J. Environ. Manage.*, **90**, S147–S160.

Harvell, C. D., Mitchell, C. E., Ward, J. R., Altizer, S., Dobson, A. P., Ostfeld, R. S., and Samuel, M. D. (2002). Climate warming and disease risks for terrestrial and marine biota. *Science*, **296**, 2158.

Hassan, M. A., Pham, T. H., Shi, H., and Zheng, J. (2013). Nematodes threats to global food security, *Acta Agric. Scandin. B*, **63**, 420–425.

Heesterbeek, J. A. P. and Zadoks, J. C. (1987). Modelling pandemics of quarantine pests and diseases: problems and perspectives, *Crop Protection,* **6**, 211–221.

Hewitt, H. J. (1998). *Fungicides in Crop Protection*, CAB International, Wallingford, UK, p. 221.

Hiddink, G. A., Termorshuizen, A. J., and van Bruggen, A. H. C. (2009). "Mixed cropping and suppression of soilborne diseases, a review", in Lichtfouse, E. (ed.), *Genetic Engineering, Biofertilisation, Soil Quality and Organic Farming, Sust. Agric. Rev.*, **4**, 119–146.

Hijmans, R. J. (2003). The effect of climate change on global potato production, *Am. J. Potato Res.*, **80**, 271–280.

Holt, J. K., Jeger, M. J., Thresh, J. M., and Otim-Nape, G. W. (1997). An epidemiological model incorporating vector population dynamics applied to African cassava mosaic virus disease, *J. Appl. Ecol.*, **34**, 793–806.

IPCC (2007). *Climate change 2007: Synthesis Report. Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Intergovernmental Panel on Climate Change (IPCC), Cambridge University Press, New York. Available at: http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf. Accessed on 23 October 2013.

IPCC (2014). Working Group I Contribution to the IPCC Fifth Assessment Report *Climate Change 2013: The Physical Science Basis*. *Summary for Policy Makers*. Available at: http://www.climatechange2013.org/images/uploads/WGIAR5-SPM_Approved27Sep2013.pdf. Accessed on 23 October 2013.

Irey, M., Gottwald, T. R., Graham, J. H., Riley, T. D., and Carlton, G. (2006). Post-hurricane analysis of citrus canker spread and progress towards the development of a predictive model to estimate disease spread due to catastrophic weather events, *Plant Health Progress*. Available at: http://www.plantmanagementnetwork.org/pub/php/research/2006/canker/. Accessed on 24 September 2014.

Jeger, M. J., Holt, J. K., van den Bosch, F., and Madden, L. V. (2004). Epidemiology of insect-transmitted plant viruses: modeling disease dynamics and control interventions, *Physiol. Entomol.*, **29**, 291–304.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**, 235–265.

Juroszek, P. and von Tiedemann, A. (2013). Climate change and potential future risks through wheat diseases: A review, *Eur. J. Plant Pathol.*, **136**, 21–33.

Kable, P. and Jeffrey, H. (1980). Selection for tolerance in organisms exposed to sprays of biocide mixtures: A theoretical model, *Phytopathology*, **70**, 8–12.

Kaukoranta, T. (1996). Impact of global warming on potato late blight: Risk, yield loss and control, *Agric. Food Sci. Finland*, **5**, 311–326.

Kirkegaard, J., Christen, O., Krupinsky, J., and Lyzell, D. (2008). Break crop benefits in temperate wheat production, *Field Crop Res.*, **107**, 185–195.

Kiselev, S., Romashkin, R., Nelson, G. C., Mason-D'Croz, D., and Palazzo, A. (2013). Russia's food security and climate change: Looking into the future, *Economics*, 2013–2016. Available at: http://www.economics-ejournal.org/economics/discussionpapers/2013-16. Accessed on 24 September 2014.

Lawes, R. and Renton, M. (2010). The land use sequence optimizer (LUSO): A theoretical framework for analysing crop sequences in response to nitrogen, disease and weed populations, *Crop Pasture Sci.*, **61**, 835–843.

Leoni, C., de Vries, M., ter Braak, C. J. F., van Bruggen, A. H. C., and Rossing, W. A. H. (2013). *Fusarium oxysporum* f. sp. *cepae* dynamics: in-plant multiplication and crop sequence simulations, *Eur. J. Plant Pathol.*, **137**, 545–561.

Leonard, K. J. (1969). Factors affecting rates of stem rust increase in mixed plantings of susceptible and resistant oat varieties, *Phytopathology*, **59**, 1845–50.

Lin, B. B. (2011). Resilience in agriculture through crop diversification: Adaptive management for environmental change, *Bioscience*, **61**, 183–193.

Lobell, D. B., Cassman, K. G., and Field, C. B. (2009). *Crop Yield Gaps: Their Importance, Magnitudes, and Causes*, NCESR Publications and Research, Paper 3. Available at: http://digitalcommons.unl.edu/ncesrpub/3. Accessed on 21 November 2013.

Lobell, D. B, Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., and Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States, *Nat. Clim. Change*, **3**, 497–501.

Luck. J., Spackman, M., Freeman, A., Trebicki, P., Griffith, W., Finlay, K., and Chakraborty, S. (2011). Climate change and diseases of food crops, *Plant Pathol.*, **60**, 113–121.

Mackenzie, S. J. and Peres, N. A. (2012). Use of leaf wetness and temperature to time fungicide applications to control anthracnose fruit rot of strawberry in Florida, *Plant Dis.*, **96**, 522–528.

Madden, L. V., Hughes, G., and van den Bosch, F. (2007). *The Study of Plant Disease Epidemics*, APS Press, St. Paul, MN, p. 421.

Madden, L. V., Raccah, B., and Pirone, T. P. (1990). Modeling plant disease increase as a function of vector numbers: non-persistent viruses, *Res. Popul. Ecol.*, **32**, 47–65.

Mancini, F., Termorshuizen, A. J., Jiggins, J. L. S., and van Bruggen, A. H. C. (2008). Increasing the environmental and social sustainability of cotton farming through farmer education in Andhra Pradesh, India, *Agric. Syst.*, **96,** 16–25.

Mancini, F., van Bruggen, A. H. C., and Jiggins, J. L. S. (2007). Evaluating cotton integrated pest management (IPM) farmer field school outcomes using the sustainable livelihoods approach in India, *Exp. Agric.*, **43**, 97–112.

Mancini, F., van Bruggen, A. H. C, Jiggins, J. L. S., Ambatipudi, A. C., and Murphy. H. (2005). Acute pesticide poisoning among female and male cotton growers in India, *Int. J. Occup. Health*, **11**, 221–232.

McCoy, R. E. (1976). A computer simulator of Ascochyta blight of chrysanthemum, *Proc. Fla. State Hort. Soc.*, **89**, 296–299.

McDonald, B. A. and Linde, C. (2002). Pathogen population genetics, evolutionary potential, and durable resistance, *Annu. Rev. Phytopathol.*, **40**, 349–379.

Michaelides, S. C. (1985). A simulation model of the fungus *Phytophthora infestans* (Mont) De Bary, *Ecol. Model.*, **28**, 121–137.

Milgroom, M. (1990). A stochastic model for the initial occurrence and development of fungicide resistance in plant pathogen populations, *Phytopathology*, **80**, 410–416.

Milgroom, M., Levin, S., and Fry, W. (1989). "Population genetics theory and fungicide resistance", in Leonard K. and Fry W. (eds.), *Plant Disease Epidemiology*, McGraw Hill, New York, pp. 340–367.

Moe, S. J., De Schamphelaere, K., Clements, W. H., Sorensen, M. T., Van Den Brink, P. J., and Liess, M. (2013). Combined and interactive effects of global climate change and toxicants on populations and communities, *Environ. Toxicol. Chem.*, **32**, 49–61.

Mundt, C. C. (2002). Use of multiline cultivars and cultivar mixtures for disease management, *Annu. Rev. Phytopathol.*, **40**, 381–410.

Mundt, C. C. and Brophy, L. S. (1988). Influence of number of host genotype units on the effectiveness of host mixtures for disease control: A modeling approach, *Phytopathology*, **78**, 1087–1094.

Mundt, C. C. and Browning, J. A. (1985). Development of crown rust epidemics in genetically diverse oat populations: Effect of genotype unit area, *Phytopathology*, **75**, 607–610.

Mundt, C. C. and Leonard, K. J. (1986). Analysis of factors affecting disease increase and spread in mixtures of resistant and susceptible plants in computer-simulated epidemics, *Phytopathology*, **76**, 832–840.

Mundt, C. C., Sackett, K. E., and Wallace, L. D. (2011). Landscape heterogeneity and disease spread: experimental approaches with a plant pathogen, *Ecol. Appl.*, **2**, 321–328.

Mundt, C. C., Sackett, K. E., Wallace, L. D., Cowger, C., and Dudley, J. P. (2009a). Long-distance dispersal and accelerating waves of disease: Empirical relationships, *Am. Naturalist*, **173**, 456–466.

Mundt, C. C., Sackett, K. E., Wallace, L. D., Cowger, C., and Dudley, J. P. (2009b). Aerial dispersal and multiple-scale spread of epidemic disease, *EcoHealth*, **6**, 546–552.

Navas-Castillo, J., Fiallo-Olive, E., and Sanchez-Campos, S. (2011). Emerging virus diseases transmitted by whiteflies, *Annu. Rev. Phytopathol*, **49**, 219–248.

Nelson, G. C., Valin, H., Sands, R. D., Havik, P., Ahammad, H., Deryng, D., Elliott, J., Fujiomori, S., Hasegawa, T., Heyhoe, E., Kyle, P., von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Muller, C., Popp, A., Robertson, R., Robinson, S., Schmid, C., Tabeau, A., and Willenbockel, D. (2013). Climate change effects on agriculture: Economic responses to biophysical shocks, *Proc. Natl. Acad. Sci.*, **111**, 3274–3279.

Nutter, F. W. Jr., Rubsam, R. R., Taylor, S. E., Harri, J. A., and Esker, P. D. (2002). Use of geospatially-referenced disease and weather data to improve site-specific forecasts for Stewart's disease of corn in the US corn belt, *Comp. Electron. Agric*., **37**, 7–14.

Pan, Z., Yang, X. B., Pivonia, S., Xue, L., Pasken, R., and Roads, J. (2006). Long-term prediction of soybean rust entry into the continental United States, *Plant Dis*., **90**, 840–846.

Pangga, I. B., Hanan, J., and Chakraborty, S. (2013). Climate change impacts on plant canopy architecture: implications for pest and pathogen management, *Eur. J. Plant Pathol.*, **135**, 595–610.

Parnell, S., Gottwald, T. R., Gilligan, C. A., Cunniffe, N. J., and van den Bosch, F. (2010). The effect of landscape pattern on the optimal eradication zone of an invading epidemic, *Phytopathology*, **100**, 638–644.

Pavan, W., Fraisse, C. W., and Peres, N. A. (2011). Development of a web-based disease forecasting system for strawberries, *Comput. Electron. Agric.*, **75**, 169–175.

Plantegenest, M., Le May, C., and Fabre, F. (2007). Landscape epidemiology of plant diseases, *J. Roy. Soc. Interface*, **4**, 963–972.

Pivonia, S. and Yang, X. B. (2004). Assessment of the potential year-round establishment of soybean rust throughout the world, *Plant Dis.*, **88**, 523–529.

Pretty, J. N. and Hine, R. (2005). "Pesticide use and the environment", in Obe, J. P. (ed.), *The Pesticide Detox: Towards a More Sustainable Agriculture*, Earthscan, London, UK.

Radcliffe, E. B. (2013). "Introduction to Population Ecology", in Radcliffe, E. B. and Hutchison, W. D. (eds.), *Radcliffe's IPM World Textbook*, University of Minnesota. Available at: http://ipmworld.umn.edu/. Accessed on 21 November 2013.

Rakotonindraina, T., Chauvin, J. E., Pelle, R., Faivre, R., Chatot, C., Savary, S., and Aubertot, N. (2012). Modeling of yield losses caused by potato late blight on eight cultivars with different levels of resistance to *Phytopthora infestans*., *Plant Dis*., **96**, 935–942.

Ramirez-Villegas, J., Challinor, A. J., Thornton, P. K., and Jarvis, A. (2013). Implications of regional improvement in global climate models for agricultural impact research, *Environ. Res. Lett.*, **8**, 024018.

Rivington, M., and Koo, J. (2010). *Climate Change, Agriculture and Food Security Challenge Program: Report on the Meta-Analysis of Crop Modeling for Climate Change and Food Security Survey*, Consultative Group on International Agricultural Research/Earth Systems Science Partnership, CCAFS Secretariat, Department of Agriculture and Ecology, Faculty of Life Sciences, University of Copenhagen, Frederiksberg C, Denmark, p. 70.

Robert C., Fournier C., Andrieu B., and Ney, B. (2008). Coupling a 3D virtual wheat plant model with a *Septoria tritici* epidemic model (Septo3D): A new approach to investigate plant-pathogen interactions linked to canopy architecture, *Functional Plant Biology*, **35**, 997–1013.

Rodrigues, R. D. Á., Juliatti, F. C., Pedrini, J. E., Fernandes, J. M. C., Justino, F. B., Heinemann, A. B., Fraisse, C. W., Farias, J. R. B., Pavan, W., Costa, L. C., do Vale, F. X. R., and Rezende, A. A. (2013). Asian soybean rust: Modeling the impact on soybean grain yield in the Triângulo Mineiro / Alto Paranaíba Region, Minas Gerais, Brazil, *Biosci. J.*, **29,** 264–279.

Roos, J., Hopkins, R., Kvarnheden, A., and Dixulius, C. (2011). The impact of global warming on plant diseases and insect vectors in Sweden, *Eur. J. Plant Pathol.*, **129**, 9–19.

Rosenzweig, C. and Parry, M. L. (1994). Potential impact of climate change on world food supply, *Nature*, **367**, 133–138.

Rosenzweig, C., Elliott, J., Derying, D., Ruane, A. C., Muller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., and Jones, J. W. (2013). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison, *Proc. Natl. Acad. Sci*., **111**, 3268–3273.

Rosenzweig, C., Iglesius, A., Yang, X. B., Epstein, P. R., and Chivian, E. (2001). *Climate change and extreme weather events — Implications for food production, plant diseases, and pests*, NASA

Publications, Paper 24. Available at: http://digitalcommons.unl.edu/nasapub/24. Accessed on 24 September 2014.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Rowthorn, R. E., Laxminarayan, R., and Gilligan, C. A. (2009). Optimal control of epidemics in metapopulations, *J. Roy. Soc. Interface*, **6**, 1135–1144.

Savary, S., Ficke, A., Aubertot, J. N., and Hollier, C. (2012). Crop losses due to diseases and their implications for global food production losses and food security, *Food Security*, **4**, 19–537.

Savary, S., Teng, P. S., Willocquet, L., and Nutter, F. W. Jr. (2006). Quantification and modeling of crop losses: a review of purposes, *Annu. Rev. Phytopathol.*, **44**, 89–112.

Savary, S. and Willocquet, L. (2000). Rice pest constraints in tropical Asia: Quantification of yield losses due to rice pests in a range of production situations, *Plant Dis.*, **84**, 357–369.

Savary, S. and Zadoks, J. C. (1992). Analysis of crop loss in the multiple pathosystem groundnut-rust-leate leaf spot. III. Correspondence analysis, *Crop Prot.*, **11**, 229–239.

Scherm, H. (2000). Simulating uncertainty in climate-pest models with fuzzy numbers, *Environ. Pollut.*, **108**, 373–379.

Scherm, H. (2004). Climate change: Can we predict the impacts on plant pathology and pest management?, *Can. J. Plant Pathol.*, **26**, 267–273.

Scherm, H. and van Bruggen, A. H. C. (1993a). Response surface models for germination and infection of *Bremia lactucae*, the fungus causing downy mildew of lettuce, *Ecol. Model.*, **65**, 281–296.

Scherm, H. and van Bruggen, A. H. C. (1993b). Sensitivity of simulated dew duration to meteorological variations in different climatic regions of California, *Agric. Forest Meteorol.*, **66**, 229–245.

Scherm, H. and van Bruggen, A. H. C. (1994). Global warming and nonlinear growth — how important are changes in average temperature?, *Phytopathology*, **84**, 1380–1384.

Scherm, H. and Yang, X. B. (1995). Interannual variations in wheat rust development in China and the United States in relation to the El Niño/Southern Oscillation, *Phytopathology*, **85**, 970–976.

Scherm, H. and Yang, X. B. (1998). Atmospheric teleconnection patterns associated with wheat stripe rust disease in North China, *Int. J. Biometeorol.*, **42**, 28–33.

Shakya, S. K., Goss, E. M., Dufault, N. S., and van Bruggen, A. H. C. (2014). Potential effects of diurnal temperature oscillations on potato late blight under climate change, *Phytopathology*. Available at: http://apsjournals.apsnet.org/doi/pdf/10.1094/PHYTO-05-14-0132-R. Accessed on 24 September 2014.

Sharma-Poudyal, D. and Chen, X. M. (2011). Models for predicting potential yield loss of wheat caused by stripe rust in the U.S. Pacific Northwest, *Dis. Control Pest Manage.*, **101**, 544–554.

Shaw, M. W. (2000). Models of the effects of dose heterogeneity and escape on selection pressure for pesticide resistance, *Phytopathology*, **90**, 333–339.

Shaw, M. W. (2009). Preparing for changes in plant disease due to climate change, *Plant Protect. Sci.*, **45**, S3–S10.

Shiferaw, B., Smale, M., Braun, H. J., Duveiller, E., Reynolfds, M., and Muricho, G. (2013). Crops that feed the world 10. Past successes and future challenges to the role played by wheat in global food security, *Food Security*, **5**, 291–317.

Shtienberg, D., Doster, M. A., Pelletier, J. R., and Fry, W. E. (1989). Use of simulation models to develop a low-risk strategy to suppress early and late blight in potato foliage, *Phytopathology*, **79**, 590–595.

Singh, M. P., Erickson, J. E., Boote, K. J., Jones, J. W., Tillman, B. L., and van Bruggen, A. H. C. (2013). Using the CSM-CROPGRO-Peanut model to simulate late leaf spot effects on peanut cultivars of differing resistance, *Agron. J.*, **105**, 1307–1316.

Singh, M. P., Erickson, J. E., Boote, K. J., Tillman, B. L., Jones, J., and van Bruggen, A. H. C. (2011a). Late leafspot effects on growth, photosynthesis, and yield of peanut cultivars of differing resistance, *Agron. J.*, **103**, 85–91.

Singh, M. P., Erickson, J. E., Boote, K. J., Tillman, van Bruggen, A. H. C., and Jones, J. W. (2011b). Photosynthetic consequences of late leafspot differ between two peanut cultivars with variable levels of resistance, *Crop Sci.*, **51**, 2741–2748.

Skelsey, P., Rossing, W. A. H., Kessel, G. J. T., and van der Werf, W. (2010). Invasion of *Phytophthora infestans* at the landscape level: How do spatial scale and weather modulate the consequences of spatial heterogeneity in host resistance?, *Phytopathology*, **100**, 1146–1161.

Sparks, A. H., Forbes, G. A., Hijmans, R. J., and Garrett, K. A. (2014). Climate change may have little effect on global risk of potato late blight, *Glob. Change Biol.*, **20**(12), 3621–3631.

Stansbury, C. D. and McKirdy, S. J. (2002). Forecasting climate suitability for karnal bunt of wheat: A comparison of two meteorological methods, *Aust. Plant Pathol.*, **31**, 81–92.

Stein, A., Kocks, C. G., Zadoks, J. C., Frinking, H. D., Ruissen, M. A., and Myers, D. E. (1994). A geostatistical analysis of the spatio-temporal development of downy mildew epidemics in cabbage, *Phytopathology*, **84**, 1227–1239.

Takle, E. S., Gustafson, D., Beachy, R., Nelson, G. C., Mason-D'Croz, D., and Palazzo, A. (2013). US food security and climate change: Agricultural futures, *Economics*, 2013-34. Available at: http://www.economics-ejournal.org/economics/discussionpapers/2013-34. Accessed on 24 September 2014.

Tao, F. and Zhang, Z. (2013). Climate change, wheat productivity and water use in the North China Plain: A new super-ensemble-based probabilistic projection, *Agric. Forest Meteorol.*, **170**, 146–165.

van den Berg, W., Rossing, W. A. H., and Grasman, J. (2006). Contest and scramble competition and the carry-over effect in Globodera spp. in potato-based crop rotation using an extended Ricker model, *J. Nematol.*, **38**, 210–220.

van den Bosch, F. and Gilligan, C. A. (2008). Models of fungicide resistance dynamics, *Annu. Rev. Phytopathol.*, **46**, 123–147.

van den Bosch, F., Zadoks, J. C., and Metz, J. A. J. (1988). Focus expansion in plant disease. II. Realistic parameter-sparse models, *Phytopathology*, **78**, 59–64.

Vanderplank, J. E. (1963). *Plant Diseases: Epidemics and Control*, Academic Press, New York.

Waggoner, P. E. (1977). Contributions of mathematical models to epidemiology, *Ann. New York Acad. Sci.*, **287**, 191–206.

Waggoner, P. E. (1981). Models of plant disease, *BioScience,* **31**, 315–319.

Waggoner, P. E. and Horsfall, J. G. (1969). EPIDEM, a simulator of plant disease written for computer, *Conn. Agric. Exp. Stn. Bull.*, **689**, 80.

Waggoner, P. E., Horsfall, J. G., and Lukens, R. J. (1972). EPIDEM, a simulator of southern corn leaf blight, *Conn. Agric. Exp. Stn. Bull.,* **729**, 84.

Waggoner, P. E. and Parlange, J. Y. (1974a). Verification of a model of spore germination at variable, moderate temperatures, *Phytopathology*, **64,** 1192–1196.

Waggoner, P. E. and Parlange, J. Y. (1974b). Mathematical model for spore germination at changing temperature, *Phytopathology*, **64**, 605–610.

West, J. S., Townsend, J. A., Stevens, M., and Fitt, B. D. L. (2012). Comparative biology of different plant pathogens to estimate effects of climate change on crop diseases in Europe, *Eur. J. Plant Pathol.*, **133**, 315–331.

Wheeler, T. and von Braun, J. (2013). Climate change impacts on global food security, *Science*, **341**, 508–513.

Wild, M. (2009). Global dimming and brightening: A review, *J. Geophys. Res*., **114**, D00D16,

Worldwatch Institute (2013). *Vital Signs 2013. The trends that are shaping our future*, W.W. Norton & Co., New York, p. 215.

Wu, B. M., Subbarao, K. V., and van Bruggen, A. H. C. (2005). Analyses of the relationships between lettuce downy mildew and weather variables using geographic information system techniques, *Plant Dis.*, **89**, 90–96.

Wu, B. M., van Bruggen, A. H. C., Subbarao, K. V., and Scherm, H. (2002). Incorporation of temperature and solar radiation thresholds to modify a lettuce downy mildew warning system, *Phytopathology,* **92,** 631–636.

Ye, L., Tang, H., Wu, W., Yang, P., Nelson, G. C., Mason-D'Croz, D., and Palazzo, A. (2013). Chinese food security and climate change: Agriculture futures, *Economics*, 2013-2. Available at: http://www.economics-ejournal.org/economics/discussionpapers/2013-2. Accessed on 24 September 2014.

Zadoks, J. C. and van den Bosch, F. (1994). On the spread of plant disease: A theory on foci, *Annu. Rev. Phytopathol.*, **32**, 503–521.

Zhu, Y.-Y., Fang, H., Wang, Y.-Y., Fan, J. X., Yang, S.-S., Mew, T. W., and Mundt, C. C. (2005). Panicle blast and canopy moisture in rice cultivar mixtures, *Phytopathology*, **95**, 433–438.

Zhu, Y.-Y., Hairu, C., Fan, J., Wang, Y., Li, Y, Chen, J., Fan, J, Yang, S., Hu, L., Leung, H., Mew, T. W., Teng, P. S., Wang, Z., and Mundt, C. C. (2000). Genetic diversity and disease control in rice, *Nature*, **406**, 718–722.

Appendix 1

This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

GUIDE FOR REGIONAL INTEGRATED ASSESSMENTS:

HANDBOOK OF METHODS AND PROCEDURES

VERSION 5.1

Guide for Regional Integrated Assessments: Handbook of Methods and Procedures

Version 5.1

AgMIP International Leaders
Cynthia Rosenzweig, Jim Jones, Jerry Hatfield and John Antle

AgMIP Team Leaders
Climate: **Alex Ruane**
Crops: **Ken Boote and Peter Thorburn**
Regional Economics: **John Antle and Roberto Valdivia**
Information Technologies: **Cheryl Porter and Sander Janssen**

AgMIP Science Coordinator
Alex Ruane (alexander.c.ruane@nasa.gov)

AgMIP International Coordinator
Carolyn Mutter (czm2001@columbia.edu)

July 17, 2014

Guidelines for Regional Integrated Assessments: Handbook of Methods and Procedures

Table of Contents

Introduction	4
Key Attributes of an AgMIP Regional Integrated Assessment	5
Core Climate Impact Questions	5
Key Regional Research Team Outputs	7
AgMIP Standardized Formats and Tools	9
Guidelines for Activities for AgMIP Regional Research Teams	10
1. Scoping of production systems and developing/refining research work plan for regional integrated assessment	10
2. Develop Representative Agricultural Pathways (RAPs) for use in regional analysis of climate impact and adaptation	11
3. Assemble existing data from experiments and calibrate crop models	15
4. Assemble and quality-control current climate series	16
5. Assemble data and simulate crop models for analysis of yield variations	19
6. Assemble economic data for regional economic analysis and develop skills for using the regional economic model	21
7. Create downscaled climate scenarios	21
8. Conduct multiple crop/livestock model simulations	24
9. Analyze regional economic impacts of climate change without and with adaptation using the regional economic model	26
10. Archive data and analyses results for integrated assessments	27
11. Disseminate integrated assessment results	28
Appendix 1. "Fast Track" Proof of Concept Integrated Assessment Exercise	29
Appendix 2. Calculating Statistics for Climate Impact Assessments Using Crop/Livestock Model Simulations with the TOA-MD Model	31
Appendix 3. Crop Model Simulations for Integrated Assessments: User's Guide	40

Introduction

The purpose of this handbook is to describe recommended methods for a trans-disciplinary, systems-based approach for regional-scale (local to national scale) integrated assessment of agricultural systems under future climate, bio-physical and socio-economic conditions. An earlier version of this Handbook was developed and used by several AgMIP Regional Research Teams (RRTs) in Sub-Saharan Africa (SSA) and South Asia (SA) (AgMIP Handbook version 4.2, www.agmip.org/regional-integrated-assessments-handbook/). In contrast to the earlier version, which was written specifically to guide a consistent set of integrated assessments across SSA and SA, this version is intended to be more generic such that the methods can be applied to any region globally. These assessments are the regional manifestation of research activities described by AgMIP in its online protocols document (available at www.agmip.org). AgMIP Protocols were created to guide climate, crop modeling, economic, and information technology components of its projects.

Various regions of the world are now undertaking regional assessments following AgMIP protocols and integrated assessment procedures. This Handbook version also has a number of modifications to the methods and to our description of methods based on what was learned from the use and evaluation of the Handbook version 4.2. However, it is important to recognize that the procedures presented here were designed for the data available to the SSA and SA teams, for implementation of two crop models per integrated assessment region (at least DSSAT and APSIM), and for use of one socio-economic model (TOA-MD) in the integrated impact assessments. Going forward, we recommend the use of multiple crop and economic models when available, based in large part to lessons learned in the various crop model intercomparisons (e.g., Asseng et al. 2013; Rosenzweig et al., 2013) and on the global economic model intercomparisions (Nelson et al., 2013). We envision that specific choices of multiple models may vary among regions, but that a core set of models should be used such that results can be aggregated and compared across all regions.

AgMIP regional integrated assessments require close coordination among economic, climate, crop modeling and IT team members within each regional team. Assessments should begin with regional teams working with stakeholders to define what outcomes are to be evaluated and then developing details of the specific production systems that need to be quantified. Each regional research team (RRT) should focus on impacts related to, at minimum, food production, income, and poverty in their regions; emphasizing important food crops and quantifying relevant uncertainties. Where appropriate, livestock components of production systems should be included. Then a plan of work should be developed by teams that will include AgMIP-recommended methods and procedures to accomplish integrated assessments and desired compatibility of outputs across regions.

This handbook was written such that it represents a minimum approach that can be expanded upon in regions where available data and resources allow. The methods and core approach used by all interdisciplinary research teams need to be fundamentally consistent in order to enable meta-analyses and large-scale studies. Particular care must therefore be

taken in introducing new methods and models that could potentially limit the ability of results to be compared beyond the immediate region.

This handbook is a living document that will continue to evolve and be improved through input from the regions as they apply it to their own situations and gain experience in the methods that are aimed at helping to unify methods and outputs.

Key Attributes of an AgMIP Regional Integrated Assessment

- Designed with input from stakeholders and policymakers
- Oriented upon production-systems-based approach (rather than specific fields) potentially including multiple crops, livestock, aquaculture, and other sources of income.
- Transdisciplinary in its linking of climate, biophysical, and socio-economic conditions and responses.
- Flexible in that its framework allows for the testing of adaptations and alternative models and methods across a series of households in a given region.
- Addresses core questions of climate impact on current and future production systems (detailed in the next section)
- Calibrated on current production system using available observed data with full and open documentation.
- Examines the impact of both mean climate changes and potential interactions with climate variability
- Presents results in a probabilistic manner with accounting of major uncertainties.
- Utilizes consistent terminology across disciplines and among various AgMIP assessments and initiatives.
- Uploads results to an online AgMIP database for archival and cross-regional analyses with full attribution of data providers and intellectual contributions.
- Publishes findings in peer-reviewed journals and disseminates information to stakeholders.

Core Climate Impact Questions

AgMIP has identified the following core research questions that motivate research activities for regional integrated assessments (**Figure 1**):

1. What is the sensitivity of current agricultural production systems to climate change? This question addresses the isolated impacts of climate changes assuming that the production system does not change from its current state.
2. What is the impact of climate change on future agricultural production systems? This question evaluates the isolated role of climate impacts on the future production system, which will differ from the current production system due to development in the agricultural sector not directly motivated by climate changes.
3. What are the benefits of climate change adaptations? This question analyzes the benefit of potential adaptation options in the production system of the future, which may offset or capitalize on climate vulnerabilities identified in Core Question 2 above.

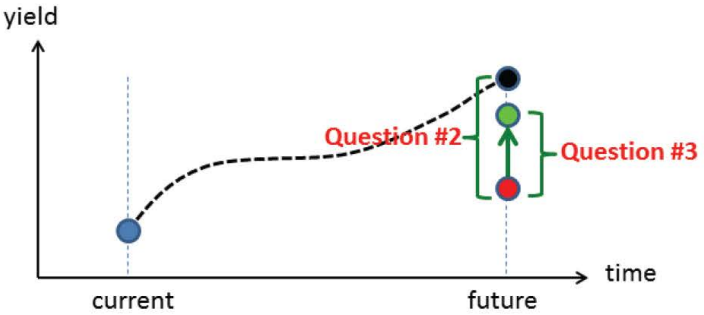


Figure 1. Overview of core climate impact questions and the production system states that will be simulated. The current production system is represented by the blue dot, while the production of the system is represented in three ways: assuming that there is no climate change (black), assuming that there is climate change and no adaptation (red), and assuming that there is climate change and adaptation (green). The dashed line represents the evolution of the production system in response to development in the agricultural sector that is not directly motivated by climate change. Core Question 2 quantifies the impact of climate change on an adaptation-free future affected by climate change, and the green line represents the benefits of adaptation in that future production system. Note that Core Question #1 cannot be depicted on this figure, as future climate impacts will necessarily encounter a different production system, however this question provides useful context on current biophysical and socio-economic vulnerability that motivates initial investments in adaptation.

As each question is designed to allow a comparison between two different production system states, **Table 1** describes the key climate, crop, and economic modeling components that will describe and compare these states.

Table 1. Overview of climate (blue color), crop model (green color), and economic model (gold color) components needed in simulation sets required to compare production system states and answer core questions #1, #2, and #3. Note that three crop model cases are defined as green numbers, and for this table the future period is assumed to be the RCP8.5 Mid-Century (2040-2069).

Core Questions	Simulation Sets	
	Current Current Climate Current Production System	**Climate Change Sensitivity** Future Climate Current Production System
1. What is the sensitivity of current agricultural production systems to climate change?	1980-2009 Climate Crop/Livestock Simulations no Adaptation (#1) TOA without RAP	2040-2069 Climate Crop/Livestock Simulations, no Adaptation (#2) TOA without RAP
	Economic Simulation #1	

Core Questions	Simulation Sets	
2. What is the impact of climate change on future agricultural production systems?	**Future without Climate Change** Current Climate Current Production System with Trend 1980-2009 Climate Crop/Livestock Simulations, no Adaptation (same as #1) TOA with RAP 1	**Future with Climate Change** Future Climate Current Production System with Trend 2040-2069 Climate Crop/Livestock Simulations, no Adaptation (same as #2) TOA with RAP 1
	Economic Simulation #2	

Core Questions	Simulation Sets	
3. What are the benefits of climate change adaptations?	**Future Climate Change without Adaptation** Future Climate Current Production System with Trend 2040-2069 Climate Crop/Livestock Simulations, no Adaptation (same as #2) TOA with RAP 1	**Future Climate Change with Adaptation** Future Climate Climate-adapted Production System with Trend 2040-2069 Climate Crop/Livestock Simulations with Adaptations (#3) TOA with RAP 1 and Adaptations
	Economic Simulation #3	

Key Regional Team Outputs

A number of outputs are anticipated from the sum of RRT activities described in this Handbook. This list of anticipated activities is intended to be used for RRT planning, and thus specific outputs and methods are provided in the material that follows. In addition, however, there are several overarching outputs that should be targeted by each RRT. These overarching outputs are summarized below, along with questions that help motivate the construction of these outputs.

a. ***A network of sites where multiple crop models have been calibrated using locally representative management, soils, cultivars, and climate to simulate food production regions that are important for regional food security, with analysis of calibration uncertainties.*** Key questions include:

- Which important farm systems, crops, and agricultural sub-regions are to be targeted for simulating regional food security?
- What data are available for calibration of crop models and for economic analyses?
- What are the crops' vulnerabilities to climate variability?
- What adaptation measures should be analyzed in the study?

b. ***A set of Representative Agricultural Pathways (RAPs) for each region for use in analyses of regional climate impacts and adaptation.*** Key questions include:
   - What output variables from global models and analyses are key drivers of agricultural trends in the region (e.g., climate, commodity prices, population growth and GDP growth from Shared Socio-economic Pathways, and global representative agricultural pathways)?
   - What key regional variables are likely to be affected by the higher level drivers (policy, socioeconomic, and technology)?
   - What quantitative trends in each of the variables are needed to parameterize agricultural models (crop, livestock, and economic) for the regional integrated assessment?
   - What qualitative storylines best describe each of these RAPs?

c. ***Characterization of historical agro-climate and climate change scenarios downscaled for use at the regional scale.*** Key questions include:
   - What are the most important factors that drive climate impacts on a given crop/region?
   - What types of climate changes are likely to impact the region?
   - What are the relative impacts of climate change and interannual variability?
   - Where are agro-climatic impacts likely to be most acute?
   - How certain are projections of future climate change?

d. ***Assessment of economic impacts for a subset of agricultural regions under future climate change, adaptation and socio-economic scenarios.*** Key questions include:
   - How will climate change affect the distribution of production, income, and poverty in the farm systems of a given region if adaptations do not occur?
   - What are the projected adoption rates of climate-adapted systems? How will various adaptations affect the impacts of climate change? How will alternative socio-economic scenarios affect the impacts of climate change?
   - How do uncertainties in key economic parameters affect the projected climate change impacts?

e. ***An adaptation package including agronomic, economic, and policy adaptations that improve outcomes under future conditions.*** Key questions include:
   - What farm-level management adaptations would be beneficial under future climate conditions?
   - What changes to the production system would increase resilience to future climate challenges?
   - How can these adaptations be represented consistently in crop and economic models?

f. ***Documentation for communication to the scientific community and to stakeholders.*** This includes web sites, databases, scientific publications, and reports that have been communicated to stakeholders.

AgMIP Standardized Formats and Tools

To ensure consistency in the archival and translation of data and results from AgMIP integrated assessment regions, several standardized data formats have been created that will be referenced in the activities below. These standardized formats also ensure compatibility with stand-alone and web-based tools that will facilitate the execution of research activities and the dissemination of integrated assessment results.

- **.AgMIP climate data format** – Standardized format for climate series at a single location, featuring daily climate data and variables needed for crop modeling.
- **Guide for Running AgMIP Climate Scenario Generation Tools with R** – This "AgMIP Climate Scenarios Guidebook" describes how to access the data and suite of scripts required to produce AgMIP climate scenarios using the AgMIP methodologies, using .AgMIP-formatted climate data for both inputs and outputs.
- **AgMIP Crop Experiment (ACE) database** – contains site-based crop experiment or farm survey data using a harmonized format based on JavaScript Object Notation (JSON). The data objects are described as key-value pairs with flexible and extensible data descriptors based on the ICASA data standards. Data can be translated from raw format to ACE and from ACE to crop model-ready formats using the QuadUI desktop utility. These data should be archived in the ACE online database through the AgMIP Data Interchange (data.agmip.org).
- **Data Overlay for Multi-model Export (DOME)** - contains datasets for field overlays, or data which were not measured at the ACE sites, but are needed for crop modeling exercises. These data are estimated based on the best agronomic knowledge of cultural practices in the region. Seasonal Strategy DOME datasets contain baseline and future management and climate inputs which are used to modify existing site data for analysis of hypothetical scenarios. Each DOME dataset will be linked to one or more ACE datasets. These data should be archived in the DOME online database through the AgMIP Data Interchange (data.agmip.org).
- **AgMIP Crop Model Output (ACMO)** – Harmonized format for results of the crop model simulations. ACMO data are linked to both ACE and DOME data. These data should be archived in the ACMO online database through the AgMIP Data Interchange (data.agmip.org).
- **Cultivar library** – This conceptual database consists of a library of cultivar parameters used for various models. The parameter sets will be stored as JSON objects, files, or links to other sources. Cultivar datasets will also be linked to ACE, DOME and ACMO databases to ensure repeatability of simulations. (Not currently implemented.)
- **Economic model input and output archives** – This repository will store input and output data for the TOA model, in the form of Excel files. Each file will be associated with one or more ACMO datasets.
- **DevRAP** – Provides a structure to guide the process to develop Representative Agricultural Pathways (RAPs), to record and document the information systematically, and to translate RAPs into model-specific scenarios. We have designed a version called DevRAP v1.0 to provide a structured format for the parameters needed to run the TOA-MD model as well as crop models.
- **AgMIP ftp site** – A temporary ftp site has been established to archive data while the interfaces for other databases are prepared. This ftp site can be accessed at ftp://data.agmip.org using the usernames and passwords assigned to each team.

- **Data Journal** – will be used to publish and permanently archive datasets which are complete and form the basis of journal articles, web visualizations, or other references. These published datasets will be assigned a DOI and can be cited with credit given to data authors, as in any other published work.

Guidelines for Activities for AgMIP Regional Research Teams

A list of characteristic activities for AgMIP Regional Projects includes eleven categories of activities along with methods that integrate across climate, crop modeling, economic, and IT teams. These are presented below. **Figure 2** shows a schematic of the overall components of the integrated assessment process. Because of the importance of close collaboration among different disciplines (climate, crop, economic and livestock if included in the systems), regional teams may want to define a subset of the overall analysis to make sure that all team members learn how to best interact with other team members to achieve the overall results. For this reason, a set of "Fast Track" steps and procedures is suggested when new regional teams are first learning how to effectively use these methods (**Appendix 1**). Here, we present the overall activities needed to perform the entire integrated assessment.

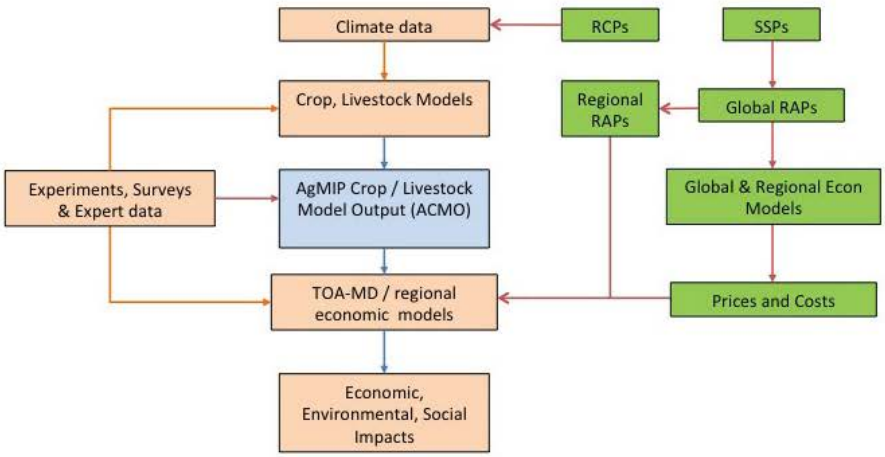


Figure 2. AgMIP Regional IA Framework: Parallel development of system design, data and modeling to couple crop & livestock models with TOA-MD.

1. **Scoping of production systems and developing/refining research work plan for regional integrated assessment.** The overall outputs from this set of activities is a report describing the region, crops selected for explicit modeling, characteristics of the broader agricultural systems, the availability of data (climate, crop, soil, and socioeconomic), and stakeholder interactions and inputs. Suggested components of this phase of the projects are as follows.

    a. **Review key project objectives, develop or refine research questions,** determine relevant stakeholders and policymakers, and assign team roles.

b. **Define key production systems** to be studied and how they influence food security in the region. Select crops and livestock that will be explicitly modeled in the study, other important components of the production system, and important sub regions that will be modeled in the study (**Figure 3**).

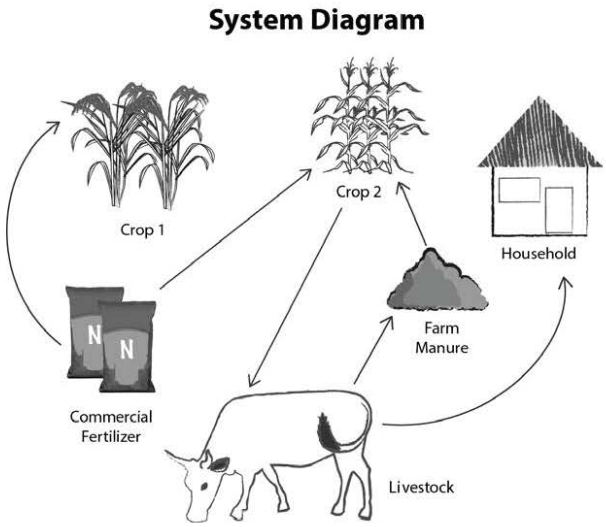


Figure 3. Example diagram describing the major elements and interactions of a production system.

c. **Select (multiple) crop models that will be used**, keeping in mind that the aim is to use at least the DSSAT and APSIM cropping system models across all regions. Assess the level of experience among team members with the selected models and identify additional capacity building needs.

d. **Become familiar with the Tradeoff Analysis Multi-Dimensional Impact Assessment Model (TOA-MD)**, the economic model that has been used in prior regional efforts, or equivalent regional economic model(s). Identify project team members who will work with the regional economic model. Evaluate regional economic model capacity-building needs and team members in the RRTs who would participate in this training.

e. **Produce a work plan that includes responsible persons, activities, time lines, and maps** of regions showing administrative boundaries, regions that will be studied, and points showing where climate and crop data are available. The report will include specifics of the information obtained in the above points, including the plan for stakeholder engagement.

2. Develop Representative Agricultural Pathways (RAPs) for use in regional analysis of climate impact and adaptation. RAPs provide an overall narrative description of a

plausible future development pathway, and also contain key variables with qualitative storylines and quantitative trends, consistent with higher-level pathways (e.g. SSPs, global RAPs developed by the AgMIP Global Modeling Group), see **Box 1**, **Box 2**, and **Figure 4**. Prices, policy and productivity trends should be consistent with the higher-level RAPs or scenarios that are available (SSPs, global RAPs, CCAFS regional scenarios). RAPs are translated into one or more scenarios (parameterizations) for the TOA-MD model and crop models. These scenarios represent a set of technology and management adaptations to climate change. These scenarios, developed for specific RAPs, will typically include changes in the types of crops or livestock produced and the way they are managed (e.g., use of fertilizers and improved crop cultivars).

Procedures for RAPs development should be based on the step-wise process as shown in **Box 1**, with input from all components (climate, crop, economic) of the AgMIP Regional Team. Outside experts may need to be consulted if there is an important area of expertise not represented within the team. Stakeholders should also be incorporated into RAPs developed, as described below.

Box 1. Overview of Step-wise Process for RAPs Development

1. A multi-disciplinary team of scientists and other experts is established.
   - Team members need to have knowledge of the agricultural systems and regions to be covered
2. The team reviews general goals and define the time period for analysis and selected higher-level pathways (Shared Socio-economic Pathways, Global RAPs) to follow the nested approach (**Figure 4**)
3. Main drivers from higher level pathways are identified (and quantified if possible, e.g. outputs from global models)
4. Based on drivers and specific agricultural systems, a draft of a title and a short narrative of a RAP is constructed
5. Based on the draft narrative, the team identifies key parameters that will likely be affected by driving forces
6. The team draft storylines for each one of the parameters (see **Figure 5**)
7. The team checks for consistency within the RAP components and with higher level pathways and models' outputs
8. Based on consistency check, agreement and confidence levels among team participants, steps 4 -7 are repeated until an acceptable draft of consistent storylines and levels of agreement and confidence are achieved.
9. The team identifies parameters that will need additional revision (expert opinion, modeled data, etc.) or that will likely be subject to sensitivity analysis.
10. The team elaborate full RAP narrative
11. The RAP narrative is documented and distributed to other experts, scientists and key stakeholders for comments.
12. The final RAPs are distributed to the modeling teams for parameters quantification and scenario development

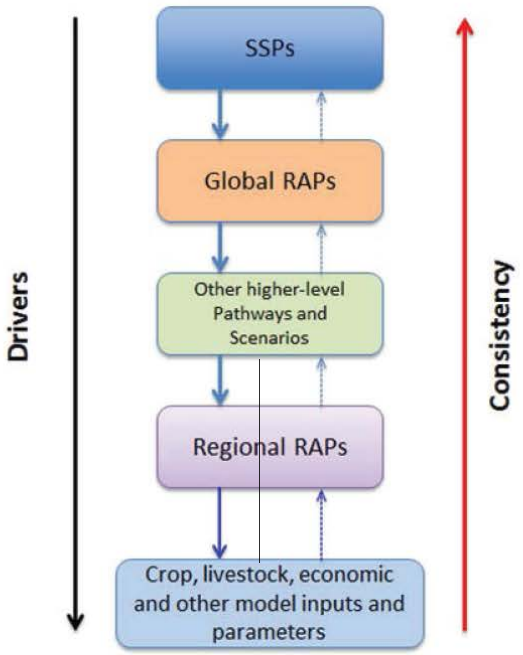
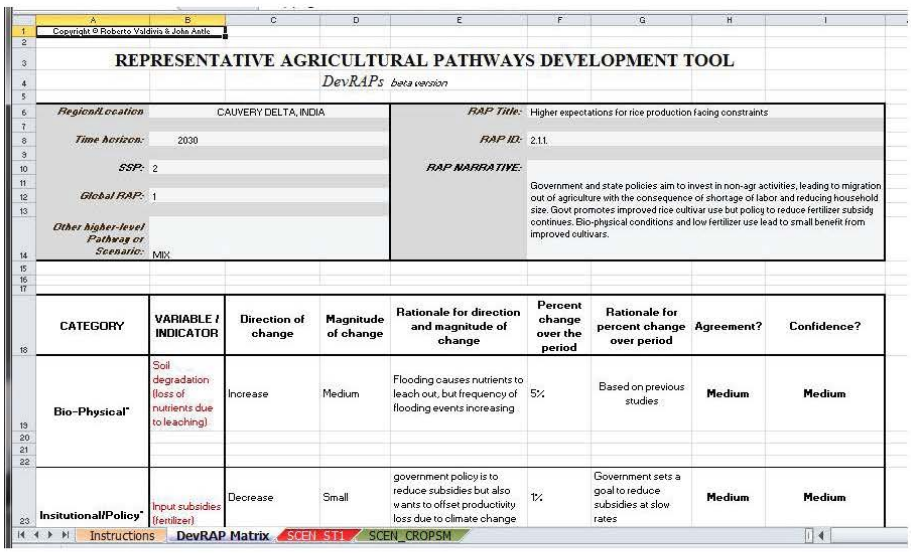


Figure 4. Developing RAPs and Scenarios: Use of a nested approach to assure consistency



Copyright © Roberto Valdivia & John Antle

REPRESENTATIVE AGRICULTURAL PATHWAYS DEVELOPMENT TOOL

DevRAPs beta version

Region/Location	CAUVERY DELTA, INDIA	*RAP Title:*	Higher expectations for rice production facing constraints
Time horizon:	2030	*RAP ID:*	2.1.1.
SSP:	2	*RAP NARRATIVE:*	Government and state policies aim to invest in non-agr activities, leading to migration out of agriculture with the consequence of shortage of labor and reducing household size. Govt promotes improved rice cultivar use but policy to reduce fertilizer subsidy continues. Bio-physical conditions and low fertilizer use lead to small benefit from improved cultivars.
Global RAP:	1		
Other higher-level Pathway or Scenario:	MIX		

CATEGORY	VARIABLE / INDICATOR	Direction of change	Magnitude of change	Rationale for direction and magnitude of change	Percent change over the period	Rationale for percent change over period	Agreement?	Confidence?
Bio-Physical*	Soil degradation (loss of nutrients due to leaching)	Increase	Medium	Flooding causes nutrients to leach out, but frequency of flooding events increasing	5%	Based on previous studies	Medium	Medium
Insitutional/Policy*	Input subsidies (fertilizer)	Decrease	Small	government policy is to reduce subsidies but also wants to offset productivity loss due to climate change	1%	Government sets a goal to reduce subsidies at slow rates	Medium	Medium

Instructions | DevRAP Matrix | SCEN_ST1 | SCEN_CROPSM

Figure 5. Screenshot of the DevRAP tool v1.0

a. **Building the RAP narratives and quantitative trends.** In this section we outline the steps to build RAPs narratives for AgMIP's regional teams. RRTs should use the DevRAP tool (See **Figure 5**) to develop and document RAPs (Valdivia and Antle 2012).

1) *Identify members of the RAPs development team.* Key members of the research team representing climate, crops & livestock, and economics. Outside members may be solicited if additional expertise is needed.
2) *Define time period for analysis*: AgMIP has designated four "time slices" in the 21st Century for analysis, current, early-century (2005-2039), mid-century (2040-2069) and late-Century (2070-2099).
3) *Select higher-level pathways:* Following the concept of a nested approach, relevant narratives and quantitative information from selected higher level pathways (e.g. SSPs, Global RAPs) need to be extracted. AgMIP regional teams are recommended to begin using SSP2 (see **Box 2** for a summary description).
4) *RAPs research process:*
    a. First meeting:
        i. Start with a "Business as usual" (BAU) RAP
        ii. Team members identify key parameters that will likely be affected by higher level pathways and draft RAP narrative
        iii. Team members are assigned variables for research
        iv. Team members conduct research –use of templates for reporting and supporting documentation. These templates can be distributed to experts for feedback
    b. Second meeting:
        i. Team members report findings and discuss storylines for each variable
        ii. BAU RAP is finalized using the DevRAP tool and complete the following information:
            1. Complete information for each parameter:
            2. Direction, magnitude & rate of change
            3. Narrative logic for changes
            4. Check for internal consistence and with higher-level pathways and models' variables
            5. Level of agreement among participants
            6. Level of confidence among participants
            7. If level of agreement and/or confidence are low, repeat process until acceptable levels are achieved.
            8. Assess whether one or more parameters need to be revised by other experts or selected for sensitivity analysis.
            9. Document source of information (pathway, model, literature, expert).
        iii. Additional RAPs are identified
        iv. Process similar to BAU is carried out with additional background research
    c. Meeting(s) to create additional RAPs –Follow similar steps as in a and b
    d. RAPs distributed to stakeholders and outside experts
5) *Modelers develop Scenarios* (see section below)

Box 2. Shared Socioeconomic Pathway #2 (SSP2) Summary: Middle of the Road

In this world, trends typical of recent decades continue, with some progress towards achieving development goals, reductions in resource and energy intensity at historic rates, and slowly decreasing fossil fuel dependency. Development of low-income countries proceeds unevenly, with some countries making relatively good progress while others are left behind. Most economies are politically stable with partially functioning and globally connected markets. A limited number of comparatively weak global institutions exist. Per-capita income levels grow at a medium pace on the global average, with slowly converging income levels between developing and industrialized countries. Intra-regional income distributions improve slightly with increasing national income, but disparities remain high in some regions. Educational investments are not high enough to rapidly slow population growth, particularly in low-income countries. Achievement of the Millennium Development Goals is delayed by several decades, leaving populations without access to safe water, improved sanitation, and medical care. Similarly, there is only intermediate success in addressing air pollution or improving energy access for the poor as well as other factors that reduce vulnerability to climate and other global changes.

Source: O'Neill et al. (2012).

b. **Quantifying Economic Model Parameters.** RAP narratives are next used to construct parameter sets for crop and livestock models and for economic models, including TOA-MD. Here we discuss creating parameters for TOA-MD using the DevRAP tool; research teams can create other parameter sheets for other models they may be using. The sheet SCEN_STi (where i=strata 1,2…) in the DevRAP tool is designed to create and document scenarios for the TOA-MD model. One or more scenarios can be constructed for each RAP as follows:
   6) *Create name and short narrative to describe the scenario*: It is important to document the key characteristics of the scenario, thus the narrative and scenario name must contain elements to understand what the scenario is about.
   7) *Identify model parameters*: The DevRAP tool includes the list of parameters used in the TOA-MD (see **Figure 3**). The team will identify the parameters that will be quantified for the specific scenario.
   8) *Quantify each parameter*: use RAP information to assign a value to each parameter. Data for these parameters can be obtained from the literature, modeled or from expert judgment, and these need to be documented.

c. **Quantifying Crop Model Management and Technology Inputs for Scenarios.** Similar to steps 6-8 above, the team will use the SCEN_CROPSM sheet in the DevRAP tool to quantify specific crop model parameters (fertilizer level, sowing density, improved cultivars, etc.) based on RAP narratives and scenario details (e.g., adaptation packages).

3. Assemble existing data from experiments and calibrate crop models. The target outputs from this set of activities are high quality data that are entered into the AgMIP ACE database and used for calibration of multiple crop models for selected sites. The data and model simulations will provide scientific evidence that the models are adapted to the crops and environmental conditions in the region and have cultivar characteristics/parameters that can be used to simulate the crops that are to be studied in the region. This is what is typically done in crop modeling training programs and in research projects. It is likely that the RRTs already have accomplished this for some subset of crops and crop models to be used in the studies. This activity is intended to document those data and past efforts, bring together new data, and ensure that the models to be used have gone through this phase of

work. It is anticipated that there will be relatively few site-years with data for any of the selected crops, but those data will be made available in the ACE database and used to improve the adaptation of crop models for the regions. Suggested components of this activity are as follows.

a. Assemble data from past experiments for calibration of selected crop models to the region for selected crops. This includes crop, soil, and climate data for site-specific experiments and field trials in the region. This will require input from crop modelers, climate, and IT project team members.

b. Input data into sentinel site ACE database for use in multiple crop models.

c. Using the AgMIP IT tools, create input files for each crop model.

d. Using methods provided by each crop modeling group (e.g., DSSAT, APSIM, perhaps others), simulate the sentinel site experiments and estimate cultivar-specific parameters to best simulate the experimental results. These results will help set cultivar characteristics and perhaps soil conditions for regional simulations to be carried out by the teams (see below).

e. Secondary focus will be estimation of productivity parameters, relative to initial conditions, crop residue, soil organic matter pools, and soil fertility for the site-specific sentinel data (NOTE: these steps will be repeated to be more appropriate for the regional simulations where site-specific information is not available).

g. Document model simulations (inputs, management, outputs, soil, climate, cultivar coefficients) by placing them in the ACE database, along with explanatory text and appropriate tables and figures showing the quality of the calibration of cultivar coefficients.

4. Assemble and quality-control current climate series. The key products from this activity will be a high-quality version of in-situ climate observations in .AgMIP format for each location where crop models will be used, a file documenting the changes made to the original raw observations, and summary maps and statistics characterizing the region being analyzed. The following methods are recommended:

a. Assemble and assess quality of station observations.

- Identify weather stations that best represent selected crop modeling regions.
- Obtain as much of the 1980-2010 period as possible (Daily precipitation, maximum and minimum temperatures, solar radiation or sunshine duration, wind speed, dew point temperature, vapor pressure, and relative humidity).
- Convert to .AgMIP units and format with missing data given a value of -99. The AgMIP format is described in the AgMIP protocols available at http://www.agmip.org.
- Name the climate series site with a 4-character code (first 2 characters from internet country code and second 2 characters representing location) following the guidelines in the AgMIP protocols (e.g. "NLHA" for Haarweg, Netherlands).

- Begin a text file to document changes made in the quality assessment and quality control of the raw files (e.g., "NLHA.info").
- Identify outlying (+/- 3 standard deviations probably deserves a closer look) and questionable data that may be corrupted. The best approach remains plotting out the dataset elements as time series to see if anything looks amiss.
- Check to see if data are plausible physically (e.g., questionable value supported by other variables), temporally (e.g., questionable value supported by preceding or following values), or spatially (e.g., questionable value supported by neighboring stations). If values are not plausible, replace with a value of -99.
- If vapor pressure, dewpoint temperature, or relative humidity correspond to a time of day other than mid-afternoon (~maximum temperature), approximate values at the time of day of maximum temperature will be computed, by conserving more robust dewpoint temperature or vapor pressures (which can be calculated using temperature at time of measurement) and then recalculating relative humidity using maximum temperature.

b. Obtain background daily climate time series (1980-2010) from the AgMERRA dataset provided by the AgMIP Climate Team (Ruane et al., in preparation). The output of this activity will be a complete set of estimated daily climate data for use in filling in missing data for observation stations. (If the observational dataset is fully complete this step may not be necessary). Until the AgMERRA dataset is fully accessible online, latitude and longitude coordinates for each location to be simulated may be sent to Alex Ruane (alexander.c.ruane@nasa.gov) to obtain this dataset in the .AgMIP format.

c. Fill in missing/flagged observation data using station observations and the AgMERRA estimated climate series. Note that two overlapping observational sets may be combined in a similar manner. This set of activities will provide a continuous, complete, physically-consistent daily climate series from 1980-2010 in .AgMIP format for use with the crop models. Suggested steps are:

- Go through station observations and fill in all data gaps as follows.
- Use simple interpolations for short data gaps (e.g., if 3 or less days are missing fill in by interpolating from good values on either side). Use caution if strong outlier exists on either side as this may not be an effective approach (e.g., if strong rain event precedes data gap we can't assume that it will have persisted throughout gap.
- For moderate gaps (e.g., 4-10 days) use background dataset to fill in gaps and bias-correct using surrounding good data (adjust mean to ensure approximate continuity with beginning and end points).
- For longer gaps use background datasets to fill in gaps and bias-correct using climatological biases calculated by comparing background dataset to good station observations (e.g., if July Tmax in background dataset is typically 0.6°C too warm, subtract 0.6°C from background dataset when filling in a July data gap; if observed rainfall is typically only 90% of background rainfall in October, multiply background dataset by 0.9 to fill in October gaps).
- Ensure that filled in data are physically plausible by checking the following:

- Relative humidity does not exceed 100%
- Relative humidity, vapor pressure, and dewpoint temperature are physically consistent at time of day of maximum temperature.
- Solar radiation is not greater than astronomical maximum (can use historical monthly maximum as proxy) or below zero.
- Maximum temperature is at least 0.1°C above minimum temperature.

d. Approximate climate time series in regions for integrated assessments. This set of activities produces a set of climate time series that corresponds to each crop or livestock modeling location in an integrated assessment region and forms the 1980-2009 (current) climate series identified in Table 1. (Note that this procedure is automated in the AgMIP Climate Scenarios Guidebook using the "farmclimate" routine). Working with the crop and economic modeling teams, recommended methods include:

- Obtain desired latitudes and longitudes for each integrated assessment site to be modeled. Name each station with a 4-character code.
- Identify as many weather stations in (or nearby) region as possible. Quality control these datasets following methods above, then assign each of the integrated assessment locations to the most representative weather station ("corresponding station" may not always be selected by geographic distance alone, but may also factor in climatic zones and/or elevation).
- If there are additional precipitation gauges (where other variables are not observed), determine which integrated assessment locations correspond to these and start with this precipitation record.
- Estimate differences in monthly climatologies between integrated assessment locations and corresponding station location using AgMERRA dataset (if distances are greater than ~50km) or WorldClim dataset (if distances are less than ~50km). Adjust corresponding station in a manner similar to the gap-filling bias adjustment to estimate integrated assessment climate series.

e. Create an AgMIP Agro-climatic Atlas for Current Period Climate. This atlas will contain maps of important agro-climatic variables for the region. Recommended methods include:

- Generate regional maps of mean temperature and precipitation during historical baseline period from observational data and from GCMs to be used in scenario generation.
- Identify agriculturally important climate metrics. If region is affected by a prominent monsoon, determine which monsoon metrics are important to regional agriculture. Compare climate information with planting rules of thumb from farmers and/or crop model configurations if possible.
- Calculate these metrics and produce maps using observational products during the historical baseline period (in consultation with local experts and stakeholders).
- Analyze uncertainty among observational products (if available) as reference for future uncertainties.

5. Assemble data and simulate crop models for analysis of yield variations. The major outputs of this series of activities include simulations of yields by multiple crop models for multiple sites within the study region. Ideally, regional projects will use on-farm survey data for which the crop models can be used to simulate each field that was surveyed. This will provide simulated results for the "matched" case where the models use climate, soil, and management for each field to simulate productivity that is then "matched" with observed yields for each field. In order to simulate each field, the teams will need to make assumptions about crop model inputs that are needed but not collected in the farm surveys. These assumed inputs should be developed with advice from agronomists in the region, and they will be documented along with the observed field survey data for each simulated result.

Crop modeling team members should analyze these matched results to be sure that they were correctly produced with well-defined and documented inputs and to be sure that results are reasonable. Invariably, there will be biases between simulated and observed survey data, and the modelers should analyze means, variances, biases, and other characteristics of the results prior to confirming that they are ready for use in the economic analyses.

A summary spreadsheet file (ACMO) will be prepared by the crop modeling team for use by the economists. This file will document all of the inputs and assumptions used in the model simulations as well as provide a summary of crop productivity outputs (e.g., yield).

If farm survey data are not available, crop modelers should work with multiple years of historical yield statistics at a district level. In this "unmatched" case, simulated yields cannot be matched one-to-one with observed farm field survey data, and variations in climate, soils, and management inputs across the region will need to be defined and sampled from. This should be done in a representative manner based on available information and expert opinion, particularly about variations in management practices across farms within the district. In this case, comparisons of crop model results will be aggregated to a district level for comparing with district yields and analyzed. Also, a report should be written on methods and results of crop model calibration, aggregation methods, uncertainty associated with seasons, and biases relative to regional aggregated yields.

Recommended steps include:

a. **Matched Case.** Assemble matched yield case data from household farm survey from sub-regions, where crop yield and minimal management (sowing date, fertilization, etc.) are available along with household economics information for 50 to 200 farmers. If it is not possible to simulate each field to produce matched outputs, crop modelers will need to use procedures for unmatched results (see 5.c. below and **Appendix 2**).
    - Follow the more detailed instructions in **Appendix 2.** You will need to enter yield survey data into Matched_Survey_Data.Import.xlsx spreadsheets and download AgMIP Tools from the http://tools.agmip.org/ website.
    - Work with regional Agronomists and Soil Scientists to identify the most likely soils for each field in the survey, and create the Field_Overlay spreadsheets that fill in the information missing from the survey, such as initial soil water, initial nitrate and ammonium, soil organic carbon degradation, fertilization dates, prior crop residue, etc. Work with Climate colleagues to identify climate information/sites.
    - Use the QuadUI tool software to convert these spreadsheets into model-ready input files for multiple crop models.
    - Use crop cultivar coefficients that have been calibrated with independent sentinel site data in the region (from procedure # 3 above).

- Simulate the matched case survey data, compute means and standard deviation of observed and simulated. Analyze simulated results by computing various statistics and compare with observed statistics, including comparison of yield distributions, means, variances, and characteristics of bias between observed and simulated yields and outliers. Depending on these analyses, crop modelers may decide to accept these inputs as baseline soils and management conditions for further analyses or they may need to make changes in the assumptions in conjunction with agronomists familiar with production in the region. Standard output files (ACMO) are used to provide crop model inputs and outputs for use by economists. See **Appendix 2** for advice on analyzing cumulate probability distributions.

b. Simulate Yields for Household Survey Farms. Using each crop model, simulate crop outputs accounting for the distribution of climate, soils, cultivars, and management present in the region for use in the economic model analyses. Crop modelers will create ACMO files that include metadata for all "production" inputs used to simulate the fields and a summary of yield results for each field. Methods include:

- A distribution of production environments and management will be determined based on the field surveys (or on unmatched distributions of inputs, see 5.d). Each RRT will determine the best source of information for creating these multiple within-region environments and management systems to best represent the inherent variability that exists in the region. This is an important decision that needs to be made by crop, climate, and economic team members working together.
- Model simulations will be conducted over the distribution of weather stations, soils information, sowing dates, cultivars, residue return, soil organic matter pools, and fertilization that represents the region being predicted. Prepare data file that contains all of the information used to produce the simulations and on key outputs such as crop yield for use by the economic team (ACMO file).
- Crop modeling teams should analyze results and write appropriate reports and publications documenting and interpreting the biophysical implications of climate change and RAP-based adaptation options that are included in the analyses.
- Document model simulations (inputs, management, outputs, soil, climate, cultivar coefficients) by placing them in the ACE database, along with explanatory text and appropriate tables and figures showing the yield probability distributions (using probability of exceedance), analyses of residuals.
- Create maps and summary statistics e.g., spatial distribution of climate, soils, management, and yields illustrated in GIS mapping methods

c. Unmatched Survey and Simulation Fields (or Regional Historic Yields). If there are no yield data available from household surveys, it will not be possible to simulate a yield for each farm as in the matched data case. In this case, crop modelers will need to work with economist team members and agronomists in the region to assemble information on variations in management and soils in the region for this "unmatched" case. Assemble soil, typical management, and typical cultivar information for the region along with long-term crop statistics data (for district level or higher) for use in evaluating crop model abilities to simulate regional yields and production. Methods for doing this are:

- Yield statistics of crops will be collected for the region over historical time periods of 30 years.

- Cultivar life cycle information will be assumed correct from the site-specific sentinel site data.
- Survey information will be collected with input of agronomists and soil scientists, to represent the distribution of weather stations, soils information, sowing dates, cultivars, residue return, soil organic matter pools, and fertilization that represents the region being predicted.
- Use QuadUI software tool (as above) to create model-ready input files for multiple crop models to simulate historic observed years as well as future climate and adaptation-RAPs scenarios.
- Similar to the matched case (5.b), crop modelers will create ACMO files for use by economists and prepare reports and publications that describe and interpret biophysical results of the study.
- For purposes of evaluating crop model abilities for simulating regional or district-level yields, crop model teams should aggregate yearly simulated results (over climate sites, soils, sowing dates, cultivars, management) to the district level yield for comparison with historical district yields (e.g., comparing distributions of simulated and observed yields, mean annual bias, etc.).
- Document model simulations (inputs, management, outputs, soil, climate, cultivar coefficients) by placing them in the ACE database, along with explanatory text and appropriate tables and figures showing the yield distributions, analyses of interannual and spatial variations.
- Create maps and summary statistics e.g., spatial distribution of climate, soils, management, and yields illustrated in GIS mapping methods

6. **Assemble economic data for regional economic analysis and develop skills for using the regional economic model.** Outputs from this set of activities include at least two economist members per project team that are capable of performing economic analyses in their respective regions and data assembled on baseline socioeconomic and agricultural production data in their regions. An output will be crop modelers and economists with experience in interdisciplinary collaboration in co-developing data sets for use by both teams (e.g., historical yields and socioeconomic survey data), with the data input to the AgMIP database. Another output is the TOA-MD model set up to simulate economic outcomes for the region, using baseline socioeconomic data. Specific steps include:

   a. Identify economic survey data and corresponding study components (see the TOA-MD model and supporting documents for further details).

   b. Work with the climate and crop model teams to produce and analyze baseline crop simulations for sites that are jointly selected for the region, based on available data from regional statistics and/or on-farm surveys. This step requires direct cooperation among disciplinary team members and relies on the above steps on collecting climate series and calibration of crop models for regional yields.

   c. Estimate economic model parameters using the available data (see the TOA-MD model and supporting documents for details).

   d. Prepare a report (following AgMIP template) describing the existing systems and documenting the data used for regional economic analysis and parameter estimates.

7. Create downscaled climate scenarios, based on AgMIP protocols, for use in the assessments of climate change studies, and provide future scenarios for use with crop

models in the AgMIP database. Note that these procedures are captured in scripts contained in the AgMIP Guidebook for Climate Scenarios. A key output from this set of activities will be future climate scenarios derived from the latest IPCC climate models and downscaled for use in the target regions. These scenarios will be in the .AgMIP climate data format and ready for multiple crop model simulations of impacts and agricultural adaptation for each region. In addition, a climate atlas will be produced of important climate variables and derived agriculturally-important indices. These atlases will include maps for use in scientific publications and for communication of results to stakeholders.

a. Create CMIP5 delta-based climate scenarios. These scenarios will be based on historical baseline daily climate data, with each day's weather variables perturbed using the changes in climate model outputs for future time periods versus those same model outputs for the historical time period. These scenarios are made using the "agmipsimpledelta" routines in the AgMIP Guidebook for Climate Scenarios, and will be created for each crop modeling site for the 5 GCMs emphasized for the core climate impact questions and for all 20 CMIP5 GCMs for the best-calibrated site in the region. Specific methods include:

- For each of these sites, calculate monthly changes in corresponding mean maximum temperature, minimum temperature, and precipitation by comparing future 30-year climate periods (AgMIP defines three main time periods: "near-term"=2010-2039; "mid-century"=2040-2069; and "end-of-century"=2070-2099) to the baseline climate period (1980-2009; use RCP 4.5 for 2006-2009 period) from the same GCM. The Mid-Century RCP8.5 is the priority period for assessment.
- Impose these monthly changes on baseline climate series for all selected sites by adding temperature changes to the baseline record and multiplying by a precipitation change factor.
- Assume that solar radiation, winds, and relative humidity are fixed at the same values that were in the historical time series. Ensure that vapor pressure, dewpoint temperatures, and relative humidity are physically consistent at time of maximum daily temperatures (warmer temperatures have higher vapor pressures and dewpoint temperature at same relative humidity).
- This will result in a 30-year .AgMIP-formatted climate series for a given future period and GCM. Scenarios should be constructed for all 20 CMIP5 climate models at the best-calibrated site in the region, while scenarios for the other crop modeling sites (farm survey sites) are only required for the 5 GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR) in focus for the core climate impact questions (identified as the 2040-2069 (future) climate series in Table 1.

b. Create AgMIP Agroclimatic Atlas that shows future climate change scenarios with uncertainties using maps with probabilities. These maps and summary results will be published and also communicated to stakeholders. Specific methods are:

- Produce region-wide maps of CMIP5 climate change projections, including median changes in mean quantities, variability, and extremes (along with corresponding uncertainties) for temperatures and precipitation.

- Also produce maps for agriculturally important climate metrics under future climate conditions for comparing with those produced for historical baseline climates.
- Place growing season temperature and precipitation changes from the 5 core question GCMs in the context of the wider CMIP5 ensemble (e.g., with scatter plots or monthly box-and-whisker diagrams).

c. Create CMIP5 mean and variability change scenarios. This activity will produce .AgMIP-formatted climate scenarios including both monthly and sub-monthly changes in temperature and precipitation. These procedures are captured in the "agmipsimple_mandv" scripts in the AgMIP Guidebook for Climate Scenarios. In many regions there are not sufficient resources or available regional climate model (RCM) results to capture important uncertainty in climate projections, however where these are available they are particularly helpful for their representation of sub-seasonal metrics that are often affected by smaller-scale atmospheric dynamics. Suggested methods include:

- Calculate monthly changes in mean maximum temperature, minimum temperature, and precipitation by comparing future 30-year climate periods to the current climate period from the same GCM/RCM combination (where available).
- Calculate monthly changes in the standard deviation of maximum temperature, the standard deviation of minimum temperature, and the number of rainy days (precipitation>0.1 mm) by comparing future 30-year climate periods to the current climate period from the same GCM/RCM combination (where available). The shape parameter of the gamma distribution for wet events may also be of interest from RCM results, but is generally not of sufficient quality in GCM simulations.
- Impose these monthly changes on baseline climate series for all sites used in the analyses using a stretched distribution approach that adjusts each event by comparing existing and desired values by distributional percentiles.
- Assume that solar radiation, winds, and relative humidity daily variables from the historical daily climate records are unchanged. Ensure that vapor pressure, dewpoint temperatures, and relative humidity are physically consistent at time of maximum daily temperatures.
- Produce mean and variability change scenarios for all 20 CMIP5 GCMs at the best-calibrated site in each region.

d. Create Near-term climate scenarios (optional). This activity will produce .AgMIP-formatted climate scenarios for the Near-term (2010-2039) period, where the influence of climate variability is likely to be at least as large as that of climate change. Methodologies and tools for this procedure are based upon Greene et al. (2012a,b). While these methods are still under development, we outline them here:

- Obtain long-term temperature and precipitation records from at least 1960-2010 (e.g., from CRU, GPCC, and University of Delaware sets) and CMIP5 GCM outputs over the 1960-2039 period.
- Calculate GCM-ensemble growing season precipitation and maximum and minimum temperatures to represent anthropogenic influence on region.

- Smooth observations for each location using 30-year smoothing window representing long-term trend and variability.
- Subtract average of smoothed observations and GCM trend from annual series of growing season observations at each location to obtain time series of natural variability (may add weight to 30-year smoothed observations if circulation anomalies or thresholds are known to have responded to anthropogenic forcing).
- Transform the natural variability time series into principal components.
- Use top 5-10 Empirical Orthogonal Functions (EOFs) to fit vector auto-regressive model, and use this model to create 10,000 years of natural variability for each site.
- Select from the distribution of decadal rainfall totals in this record and from the distribution of CMIP5 GCM trends in order to create a 30-year Near-term scenario designed to examine particular vulnerabilities in the agricultural sector.
- Construct a daily time series in .AgMIP format that matches the seasonal properties in the Near-term scenario using analog months from the AgMERRA daily climate series used in Activity 4 above.

8. Conduct multiple crop/livestock model simulations at all crop/livestock modeling locations for the three cases identified in Table 1: #1) current climate with current production systems technology, #2) future climate scenario(s) with current production technology (no adaptation), and #3) future climate scenario(s) with adaptation. In addition, examine full GCM ensemble for a single, best-calibrated and representative site in each integrated assessment region (these latter results will not be passed on to economic analysis). Outputs should be reviewed by crop modeling team members working closely with economic and climate team members to ensure the results are plausible, e.g., that there are no unexplained outliers. When the team has finalized the crop model simulations and summarized outputs in the ACMO file, outputs from the three cases will be used by the economists in the TOA-MD economic model, and outputs from the single location GCM ensemble simulations will be used by the climate team members to place the subset of GCMs in context.

a. Simulate yield distribution across all farms for the core climate impact question cases. This includes simulation of responses across GCMs, farms, and across years within the 30-year periods. Multiple crop/livestock models will be used to simulate variations in climate, soils, and management, thus obtaining within-region variability of production. These results will be put into the AgMIP ACMO database for use in the economic analyses.

- *Case #1: Current climate with current production systems technology*: Simulate current period climate series (identified as planting years 1980-2009 in Table 1) for all farms using the 30-year climate series created in Activity 4 above, current production systems and a CO_2 concentration of 360ppm for all years (see Table 2).
- *Case #2: Future climate scenario(s) with current production technology (no adaptation)*: Simulate future period climate delta-based climate scenarios (beginning with RCP8.5 Mid-Century, identified as planting years 2040-2069 in

Table 1) for all farms using the 30-year climate series created in Activity 7 above, current production systems and a CO_2 concentration corresponding to the central year for all simulations (see Table 2). Run scenarios for at least the following GCMs: CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR. This GCM subset was selected to save resources due to their long history of development and evaluation, a preference for higher resolution, and established performance in monsoon regions.

- Organize simulated yields and enter those results into the AgMIP Crop Model Output database (ACMO), which contains variables needed by the economic team members for the regional economic model analyses.
- Create and document an adaptation package via collaboration between the crop and economic modeling team. Adaptations connected to vulnerabilities identified in a comparison between Case #1 and Case #2 results are preferred (e.g., heat or drought-tolerant cultivars; dramatically shifted sowing dates; added irrigation; subsidies for improved seed). Improved management that is not directly linked with climate impacts on the region are better handled as part of the representative agricultural pathway that defines future production systems prior to climate change adaptations.
- *Case #3: Future climate scenario(s) with current production technology with adaptation*: Simulate future period climate delta-based climate scenarios (beginning with RCP8.5 Mid-Century, identified as planting years 2040-2069 in Table 1) for all farms using the 30-year climate series created in Activity 7 above, current production systems plus the adaptation package identified above in Activity 8a and a CO_2 concentration corresponding to the central year for all simulations (see Table 2). Run scenarios for at least the following GCMs: CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR.
- Summarize yield impacts in tables, graphs, and maps for publication and communication to stakeholders. Included in these tables, graphs, and maps should be:
  - within-region variability in impacts, and
  - uncertainties associated with crop models and climate models
  - Interpret reasons for variations among crop and climate models and households

Table 2: Central year carbon dioxide concentrations for AgMIP climate scenarios and time periods, with the Current and RCP8.5 Mid-Century time periods highlighted as they will be the primary focus of integrated assessment. These are the concentrations to be used for all years in a given scenario experiment.

Scenario and Time Period	Planting Year Coverage	Mid-year	[CO2]
Current	**1980-2009**	**1995**	**360 ppm**
RCP4.5 Near-term	2010-2039	2025	423 ppm
RCP8.5 Near-term	2010-2039	2025	432 ppm
RCP4.5 Mid-Century	2040-2069	2055	499 ppm
RCP8.5 Mid-Century	**2040-2069**	**2055**	**571 ppm**
RCP4.5 End-of-Century	2070-2099	2085	532 ppm
RCP8.5 End-of-Century	2070-2099	2085	801 ppm

b. Simulate impacts of full ensemble of climate changes from all 20 CMIP5 GCMs on single, best-calibrated site in integrated assessment region. Compare climate impacts from all 20 GCMs using both delta-based (mean changes only) and mean-and-variability scenarios, place the 5 GCM-subset in this broader context, and estimate influence of variability changes. If these simulations suggest that variability changes are substantially important, these scenarios may be used instead of the delta-based scenarios for core question economic analysis if resources allow.

c. Simulate impacts from Near-term climate scenarios (optional). Conduct simulations for planting years 2010-2039 at the best-calibrated and most representative site using the Near-term climate scenarios created in Activity 7 above.

9. Analyze regional economic impacts of climate change without and with adaptation using the regional economic model. Outputs will be impacts of climate change on agricultural production, farm income and poverty, and projected rates of adoption of adapted systems. To the extent possible, teams should use these results of these sub-national analyses to draw implications for the national impacts, e.g., by extrapolating impacts to regions with similar production systems. The AgMIP regional integrated assessment framework is summarized in **Figure 1.**

a. Economist team members will use the methods outlined in Appendix 2 to use crop model simulated yields to estimate regional economic model parameters.

b. **The economist team members will use the TOA-MD (or similar) regional economic model to analyze the impacts of climate change** for each of the economic model simulations identified in Table 1, using crop/livestock model cases #1-#3, which together address the three core climate impact questions:
   - *1. What is the sensitivity of current agricultural production systems to climate change?*
   - *2. What is the impact of climate change on future agricultural production systems?*
   - *3. What are the benefits of climate change adaptations?* For this analysis the economists will first work with the crop modeling team to identify an adaptation package that includes crop/livestock and economic model parameters representing adaptations designed to address climate vulnerabilities and opportunities identified in questions 1 and 2 above.

c. These results will be summarized with graphs and reports for scientific publications and for dissemination to stakeholders.

10. Archive data and analyses of results for integrated assessments

An important output of integrated assessments will be databases for the regions that will include climate, soil, management, experiments, surveys, regional economic model parameters, and historical yields that will have been used for the analyses in this set of

projects that will be highly valuable for additional future analyses as models improve, research and policy questions change, and adaptation approaches evolve. These archived data will be available for broad use, although it is recognized that some data used in the projects (such as daily climate data in some cases, or confidential survey data) may not be archived due to intellectual property rights and data policies. Additionally, archived results from climate, crop models, and economic models will serve as the source for various publications and presentations, including web-based information that will be made available for stakeholders. A well-documented archive of AgMIP experiments, outputs, and analysis tools will facilitate future improvements in capabilities to perform integrated assessments of climate change impacts and adaptation at site and aggregated scales.

Figure 4 presents a data flow diagram for AgMIP Regional Integrated Assessments. Data created using the tools and procedures outlined in this document should be archived in AgMIP databases. Research teams shall contribute data to ACE (AgMIP Crop Experiment), DOME (Data Overlay for Multi-model Export), ACMO (AgMIP Crop Model Output) and Regional Economic databases. The AgMIP IT Team will provide tools and training through the regional workshops and web tutorials so that RRTs can interact with the ACE, DOME , ACMO and regional economic databases directly through the AgMIP Data Interchange (data.agmip.org) which connects to AgMIP data nodes. This will allow for storage of standardized databases of crop experiments and yield trials for the region and outputs of crop model simulations.

Data to be archived includes:

a. Climate data
    - Observed weather data for crop model calibration
    - 1980-2010 quality-controlled daily climate data for use in the AgMIP regional assessment
    - future ensembles of daily climate scenarios
b. Crop Modeling
    - Harmonized (ACE and DOME) data associated with detailed calibration data from field experiments or other sources.
    - Calibrated cultivar parameters
    - Soil parameters as modified by modelers used in simulations
    - Harmonized data associated with farm survey sites for regional assessments using baseline and future conditions (ACE and DOME data)
    - Crop model outputs for survey, baseline and various future climate conditions (ACMO data)
    - Text summary of climate impacts on yield, considering crop management in survey fields
c. Economic data
    - Inputs to regional economic models (including survey metadata)
    - DevRAP matrix spreadsheet including output data from global economic models used in the RAPS and productivity trends – csv format.
    - Regional economic model outputs - Impacts of climate change on agricultural production, farm income and poverty, and percentage of winners and losers and predicted adoption rates of adapted technologies in spreadsheet format.

A desktop utility is under development that will combine all of the steps required for a regional assessment researcher to input and manipulate farm survey data and convert to ACE format, create field overlay and seasonal strategy DOMEs, generate model-ready data for the user's models of choice, harmonize simulated model outputs into ACMO format, and

store all data to the server in linked ACE, DOME and ACMO databases. Users will also be able to use the utility to query the databases for existing datasets. The utility is a combination of the spreadsheet template data entry, ADA, QuadUI and ACMOUI with additional linkages to the online databases.

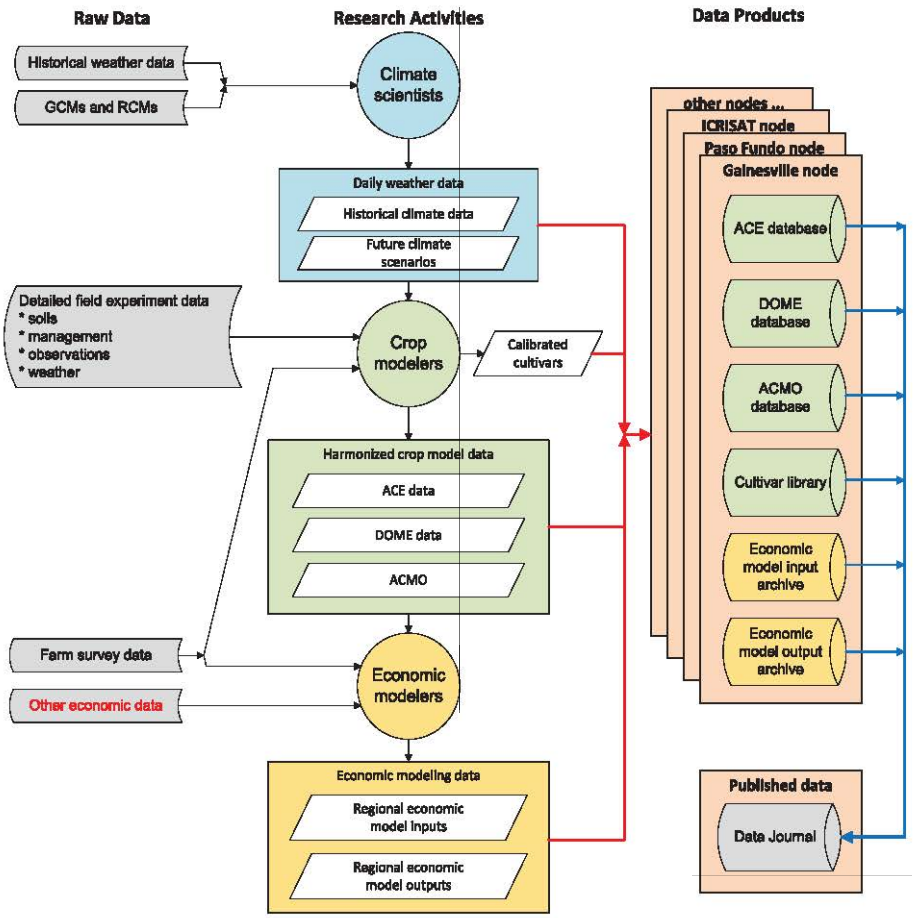


Figure 4. Data flow diagram for AgMIP Regional Integrated Assessments showing AgMIP data products and archive databases

11. Disseminate integrated assessment results. The key outputs from this set of activities include scientific publications, project reports, results summarized on regional web pages linked to the AgMIP web site, and workshops with stakeholders. Initial and ongoing interaction with stakeholder and policymaking communities are likely to be as valuable as

the dissemination of results to these communities, as early and consistent interactions increase buy-in and help develop a more useful and efficient research project

a. Develop RRT-specific web pages for the AgMIP web site. The AgMIP IT Team will provide information on how to create region-specific web pages and will give regional IT team members access to create and maintain that web information. Each region will have its project goals and methods on the site as well as pictures of project activities, output tables, maps, and graphs, as well as news items, for example.

b. Conduct project workshop with stakeholders.

- Invite stakeholders to SSA and SA workshops
- Organize stakeholder sessions at a region-specific workshops to keep them informed and learn from them what information they need for their planning and policy-making responsibilities

c. Prepare scientific publications. AgMIP research is designed to provide results that are well-suited for peer-reviewed journal publications and informing national and regional publications related to climate vulnerabilities, economic development, and adaptation/mitigation planning relative to food production and food security.

Appendix 1

"Fast Track" Proof of Concept Integrated Assessment Exercise

Because of the coordination needed among different science disciplines in the AgMIP regional integrated assessment efforts, each AgMIP regional team should perform a "proof of concept" assessment on a fast track to help everyone on the regional teams to understand their roles and the interactions that must take place among different disciplines. Accomplishing this will ensure that the mechanics of the process are understood and functioning, at which point it will be easier for all teams to proceed with their further, more detailed assessments.

To do the fast track integrated assessment exercise, the team should select only one subregion, one crop, one crop model, and one climate site location; then simulate crop yields using the historical climate data for that one location and also simulate crop yields for one climate change scenario for the time period of 2040 – 2069 using the methods described above. Additional details are:

a. The entire regional team should identify one small sub-region where the fast track assessment will be performed. Ideally, the sub-region should be an area in which household survey data are available with at least one climate data site within the area and where there are experimental data available in or nearby the area that can be used for calibrating one (or more) crop models.
b. The crop modelers will parameterize the crop models using available data from experiments, if this has not already been done. This will provide parameters for cultivar types that are currently being used in the region.
c. The economists should describe the site characteristics, including a map showing the farms and including management and farm characteristics.
d. Economists will provide the socioeconomic data, including farm site locations, to the crop modelers so that they can assemble the needed crop model inputs to run the crop models. Ideally, the socioeconomic survey data would have data on crop management practices (planting date, N application amounts) and on crop yield. For example, there may have been 80 farms surveyed with such data, and those farms would be used to assemble crop model input data for each farm, similar to the Machakos example that was used to demonstrate the approach.
e. The climate team members in the region will prepare and clean the historical climate series for one station in the region. This site will act as the baseline climate series for all crop modeling and analysis in the fast-track (including surrounding farms), and will also serve as the basis of one climate change scenario generated using the basic delta method that represents projected GCM changes. These climate series may be used in the crop model runs to compute the impacts of climate change (assuming no adaptation for this fast track).
f. The regional crop modelers will prepare input files for running one selected crop model (DSSAT or APSIM preferably) for each farm location in the selected study site/area. This includes assembling representative soils for the sites. The crop modelers will simulate each of the fields in the farm surveys, analyze simulated results relative to observed yields to evaluate reliability of results, and prepare a model output file ACMO) for documenting model inputs and outputs for use by economists in the TOA-MD analyses.
g. If socioeconomic data do not include farm site yields, then the crop modeling team members will use the procedures for calibrating and evaluating crop models for use in simulating mean yields for district or other administrative unit (see section 5c in this handbook). This alternate procedure will provide crop models ready for use in the region with estimates of average bias.

h. The crop modelers will then simulate yields for each of the farm sites in the selected area using historical climate data (1980-2009 planting years) and repeat the simulations using the one selected climate scenario's climate file. The modelers will assess yield results, evaluating how reasonable they are and produce an AgMIP Crop Model Output file (ACMO) that will be used by the economists in the TOA-MD analysis.
i. The economic team members will take crop model results and use the TOA-MD model to analyze the impacts of the climate change scenario on the distribution of economic impacts for the area.
j. The entire team will meet to evaluate the entire process and to discuss and interpret the results.
k. After the proof of concept study, the team will be ready to design its assessments of impacts and adaptation options based on the RAPs, more advanced climate scenarios, and a better representation of climate and crop model uncertainties.

Table 1. Regional Research Team Activities. This is a checklist of activities that should be coordinated across team members in each RRT such that each RRT can produce comparable integrated assessments, as noted in the timeline of activities.

Task
1. Scoping of cropping systems and developing/refining research work plan
2. Develop Representative Adaptation Pathways (RAPs) for climate change
3. Assemble Existing Data from Experiments and Calibrate Crop Models
4. Assemble and Quality Control Historical Baseline Climate Series.
5. Assemble Data and Simulate Crop Models for Analysis of Yield Variations.
6. Assemble Socioeconomic Data; Develop Skills for Regional Economic Analyses
7. Create Downscaled Climate Scenarios
8. Simulate Productivity Impacts of Climate Change; Analyze Adaptation Options
9. Analyze Economic Impacts of Climate Change and Adaptation Approaches
10. Archive Data and Analyses Results for Integrated Assessments
11. Disseminate Integrated Assessment Results

Appendix 2

Calculating Statistics for Climate Impact Assessments Using Time-Averaged Crop/Livestock Model Simulations, RAPs and the TOA-MD Model

John Antle and Roberto Valdivia

February, 2014

Introduction

This document describes how crop model simulations and Representative Agricultural Pathways can be used with TOA-MD to implement assessments of climate change impact and adaptation using "matched" and "unmatched" data from crop or livestock simulation models. We use the case of a population of heterogeneous farms with a single stratum and one production activity to illustrate the methods. This appendix presents methods for the use of data from crop or livestock models to simulate climate impacts by averaging data over time within the "current period" and within the "future period" defined for the analysis.

It is important to recognize that the methods presented here are not designed to represent temporal variability within the current period or within the future period. We focus on the time averaged case because of key limitations of the data that are usually available. In most cases, we *do not* observe yields or management over enough years to measure variation over time for individual farms. Thus, our methodology is designed to use cross-sectional survey data to estimate spatial heterogeneity reflecting bio-physical differences and management differences across farms.

The first section presents concepts and definitions. The second section describes the calculations used to estimate the parameters of the TOA-MD model.

1. Concepts, Definitions and Assumptions

The Three Core Questions

The methods described here can be used to answer the three "core questions" described in the first part of this Handbook: climate sensitivity analysis in current world conditions (question 1); impact of climate change in future world conditions (question 2); adaptation to climate change in future world conditions (question 3). Note that the TOA-MD model can also be used to analyze the adoption of adapted technologies under current conditions, but that type of analysis is not part of the Core Questions for climate change analysis.

Incorporating Spatial and Temporal Variability

We know yields and related outcomes (economic returns) vary over space and time, and this variation is important to understand vulnerability of farms to climate change. Therefore we need to project these distributions into the future for climate impact assessment.

We can describe a variable such as a yield for a production system h used at location j at time t as y_{hjt}. Let μ_{hj} be the mean for farm j obtained by averaging its values of y_{hjt} over time and let μ_{ht} be the mean for year t obtained by averaging y_{hjt} over all farms in that year. We will say that μ_{hj} is the *time-averaged* mean for farm j and μ_{ht} is the *spatially-averaged* mean

for year t. Similarly, we can decompose the variance of y_{hjt} into spatial and temporal components. To obtain meaningful approximations to the distribution of outcome variables for the TOA-MD model, we often need to stratify populations of farms that come from different sub-populations or different time periods. For example, in a given year, we may need to stratify farms geographically or by socio-economic characteristics such as size or ownership of livestock.

Our goal is to use the available data to estimate these variances using the data we have:

- Farm survey data that provide observations of current yields, management and other variables.
- Secondary data on average yields for the study region.
- Projected yield growth rates from global agricultural economic models or RAPs.
- Current and future simulated yields that are based on observed soils and management, and current and future projected weather.

A key limitation of the data is that, in most cases, we *do not* observe yields or management over enough years to measure variation over time for individual farms. Thus, our methodology is designed to use our cross-sectional survey data to estimate spatial heterogeneity reflecting bio-physical differences and management differences across farms.

Defining the Study Region, Time Periods and Systems

The presentation here is for the analysis of a farm population in an "integrated assessment region," i.e., a study area defined geographically and possibly in terms of other socio-economic characteristics. Our convention for time t is that it represents a calendar year. The current period covers t = 1,…,T years, and the future period is F years ahead of year 1, and thus covers years t = F+1,…,F+T. Following the TOA-MD terminology, we use a subscript h = 1,2 to index the farm system which is composed of the household and the agricultural production system which can include crop, livestock and aquaculture sub-systems.

Note that the interpretation of system 1 and system 2 depends on the type of analysis being done. For the purpose of calculating the effects of climate change on productivity, we interpret system 1 as the current production system in the current period and system 2 as the same system if it were observed in use with the future climate. However, for analysis of the three questions, system 1 and system 2 are constructed to represent various combinations of climate change effects, socio-economic conditions and technologies.

To further simplify this presentation, we consider the case of a production system that has a single activity (say, a crop). More generally, the same types of calculations would be applied to each activity in each sub-system (i.e., to all crops, all livestock, all aquaculture activities).

In most cases available farm survey data will come from a year (or years) near the end of the current period used for climate data and bio-physical model simulations, and management data used in these simulations will come from these survey data. For example, AgMIP's Regional Research Teams are using 1980-2009 as the current period for climate data and crop and livestock simulations. However, most survey data being used are from 2005 or later. For the economic analysis, using a 30-year period as "current" is not practical due to data limitations, the challenges of dealing with real and nominal trends, etc.

Therefore, for the economic analysis, we are using the most recent 5-year period centered as closely as possible on the year(s) of the economic survey data for purposes of defining the "current period."

Basic Variable Definitions

t = time (calendar year)

F = beginning of future time period (year)

T = length of current time period C and future time period F (years, first year = 1)

h = system index = 1,2

j = farm index, j = 1,…,J farms in data sample representing the integrated assessment region study area

k = year when survey data were collected

p_h = representative output price (currency units/kg) in the current or future period

y_{hjt} = crop yield (kg/ha)

μ_{1j} = time-averaged mean of yields y_{1jt} for farm j for the current period

μ_{2j} = time-averaged mean of yields y_{2jt} for farm j with climate change

Y_{1k} = mean of observed yields y_{1jk} in the survey data for current year k

Y_1 = mean of yields averaged over all years in the current period, obtained from secondary data in the study area

$\beta_{yk} = Y_1/Y_{1k}$ = normalization factor used to scale survey data yields to the current period mean

s_{hjt} = simulated crop yield for system h, farm j in year t (kg/ha)

s_{1j} = simulated crop yield for farm j time-averaged over the current period

s_{2j} = time-averaged simulated crop yield with climate change for farm j

$b_{hjt} = s_{hjt}/y_{hjt}$ = bias in simulated crop yield (note, can only be observed for current period)

$r_j = s_{2j}/s_{1j}$ = relative yield for farm j

a_{hjt} = total crop area on the farm (ha)

R_{hjt} = revenue = $p_{ht} \cdot y_{hjt} \cdot a_{hjt}$ (currency units/farm/time)

R_{hj} = time-averaged revenue (currency units/farm)

C_{hjt} = production cost (currency units/farm/time)

$\kappa_{hjt} = C_{hjt}/a_{hjt}\, y_{hjt}$ = average production cost (currency units/kg)

$m_{hjt} = (p_h - \kappa_{hjt})/p_h$ = profit margin (%)

C_{hj} = time-averaged production cost (currency units/farm)

C_1 = mean of production cost averaged over all years in the current period, obtained from secondary data in the study area (if available)

$\beta_{ck} = C_1/C_{1k}$ = normalization factor used to scale production cost survey data to the current period mean (note, If β_{ck} can't be estimated, then use $\beta_{ck} = \beta_{yk}$ to assume that production costs from survey data deviates from what is representative for the current period and costs are normalized by the same factor as yields; or use $\beta_{ck} = 1$ when cost data is representative for the current period).

$G_{hjt} = C_{hjt}/R_{hjt}$ = production cost relative to revenue (unit-free)

$G_{hj} = C_{hj}/R_{hj}$ = time-averaged production cost relative to time-averaged revenue (unit-free)

$V_{hjt} = R_{hjt} - C_{hjt}$ = crop net returns for the farm (currency units/time)

V_{hj} = average of V_{hjt} over current or future time (currency units)

The Relative Yield Model

We use both survey data and simulated data to represent the effects of climate change on productivity using the *relative yield model*. The idea behind this model is as follows: suppose we interpret system 2 as the current system being used under conditions of a future climate, and we interpret system 1 as the current system being used under conditions of the current climate. The average yield under climate change can then be related to the mean of the current system as $\mu_{2j}/\mu_{1j} = r_j$. We define r_j as the *relative yield under climate change*. We assume that we can approximate a yield impacted by climate change by estimating r_j with crop model simulations as s_{2j}/s_{1j}, where s_{2j} is the time-averaged simulated yield for farm j under climate change, and s_{1j} is the time-averaged simulated yield for farm j in the current period. Then we project the yield with climate change as $y_{2jt} = r_j \cdot y_{1jk}$ where y_{1jk} is the observed yield from a farm survey in the current year k for farm j.

Matched and Un-Matched Data

Two situations may be encountered with analysis using this type of farm survey data:

Matched Data: a crop yield can be simulated for each survey farm, for each crop in the system for which a crop model is available. This is true when weather and soil data can be associated with each survey farm, and some crop management data are included in the survey.

Data matching is possible in most cases where farm survey data are available and some kind of information is included in the survey to identify the survey farms' locations. Ideally, the spatial identifier is the farm's spatial coordinates (or even better, the centroids of individual fields). Note that when spatial coordinates are not included in a survey, they can be approximated with other location identifiers. For example, a legal address or village name may be available, and this may be used to approximate the spatial coordinates of the farm.

It is important to note that the matching of weather and soil data to survey farms will typically require using the *best approximation possible given available data*, because farm-specific weather and soils data are almost never available. Nevertheless, **as long as weather and soil data can be assigned to each survey farm through some reasonable procedure,**

the term "matched data" is used, because with the farm specific management data, it is possible to simulate yields for each farm.

Un-Matched Data: a distinct crop yield ***cannot*** be simulated for each survey farm; however, spatially varying weather and soil data are available to run crop model simulations with representative management for the region.

Note that in the un-matched case, it is possible to estimate a simulated yield *distribution* that corresponds to the population of farms represented by the survey; however, it is not possible to match simulated yields to the survey farms.

RAPs: Accounting for Future World Conditions

RAPs are used to represent future conditions, including productivity trends and effects of future economic conditions on output prices and costs of production. Regional RAPs must incorporate trends (e.g. yield trends from global econ models) following the methodology presented below, to translate current production systems into the future conditions defined by a RAP.

Parameters needed for Question 2

The following parameters *are used to adjust for future trends, if appropriate. They can derived from model projects or RAPs as appropriate.*

Γ = compounded yield growth factor between current and future periods. Used to estimate trended parameters of system 1 for Core Question 2 (e.g. use AgMIP Reference scenario data from IMPACT global model).

ϕ_h = compounded price growth factor between current and future periods. Used to estimate trended output price parameters.

- When h=1, ϕ is the price growth factor WITH NO climate change and it is used to estimate parameters for system 1 for **Core Question 2** (e.g. use AgMIP Reference scenario data from IMPACT global model).
- When h=2, ϕ is the price growth factor WITH climate change and it is used to estimate parameters for system 2 for **Core Question 2** (e.g. use SSP2_HGEM_DSSAT_5crop scenario from IMPACT global Model)

Ψ = compounded variable production cost growth factor between current and future periods. Used to estimate trended parameters of system 1 **for Core Question 2.** This factor should be defined as part of the RAPs.

Parameters for Core Question 3

Note that System 2 for Question 2 is the same as System 1 for Question 3. For System 2 of Question 3, we begin with System 1 and modify the parameters to represent the adapted technology (including changes in yields and costs). Thus, for System 2 of Question 3, when calculating the relative yield the numerator should be obtained from the crop or livestock model simulations for the adapted technology. For components of the system that do not have crop or livestock models, estimates of the productivity effects of the adaptation must be obtained from other information such as the RAP or other research in the literature.

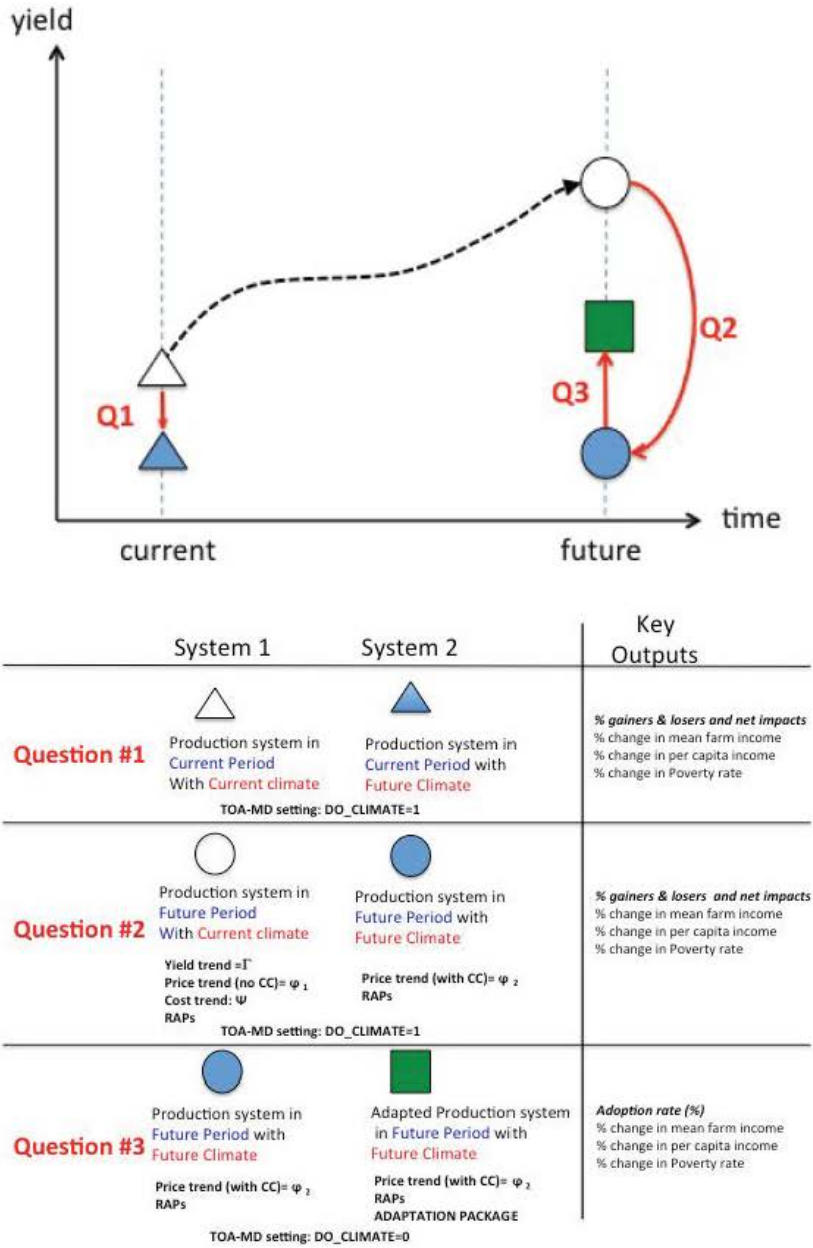


Figure x. Overview of core climate impact questions and the production system states that will be simulated and key economic components and output indicators for TOA-MD simulation runs. Note: For illustration purposes the figure on top assumes negative climate change impacts on yields. Some regions may have positive impacts of climate change on yields.

Key Assumptions

A1: *The distribution of μ_{1j} (the true time-averaged mean of farm j in the current period) is approximated by the distribution of y_{1jk} in the current year k in which the spatial yield distribution is observed.* This assumption allows us to use the observed yield in year k, normalized to the mean of the current period, as a proxy for μ_{1j}. However, since we know that the observed yields for each farm will vary from the average in the current period, we know that the projected future yields include this variation. Thus, we need to take care in using data from the current period. The more years of data that can be used, the more we can average out the individual-year variation from the current period data, and doing so should result in better estimates of μ_{1j} and thus better projections of future yields.

A2: *Crop simulation biases are the same in the present and future, implying they are location-specific but time invariant, i.e., $b_{hjt} = b_j$ for all j.* Since we cannot observe future biases, there is no way to relax (or invalidate) this assumption (although, we could test its validity with historical data). Note $s_{hjt} = b_j\, y_{hjt}$; thus A2 implies that we can use relative simulated yields to approximate relative actual yields because $s_{2jt}/s_{1j} = b_j\, y_{2jt}\,/b_j\, \mu_{1j} = y_{2jt}/\mu_{1j} = r_{2jt}$. The same logic follows for the time-averaged relative yield r_j.

A3: *$G_{1jt} = G_{2jt} = G_{1j}$. The ratio of cost/revenue is the same in systems 1 and 2 for all years.* Note, this is equivalent to the assumption that average cost per unit of output, κ_{hjt},is a constant across farms and time that is proportional to output price; i.e. $C_{hjt} = \kappa_{hjt} * y_{hjt}{}^* a_{hjt}$, $\kappa_{hjt} = \kappa_h$ for all j and t, and $\kappa_1/p_1 = \kappa_2/p_2$. Equivalently, this is the assumption that the profit margin m_{hjt} is the same in the present and the future. This assumption provides a standardized way to project future cost based on current costs, but note that this assumption can be modified to fit a future situation where costs are expected to deviate from this relationship. For example, if labor costs are a large share of cost of production and are expected to increase faster than output price, the analyst might assume that $\kappa_1/p_1 < \kappa_2/p_2$ or that the profit margin is lower in the future.

A4: *Yields in the integrated assessment region grow at rate γ, and crop model simulations for the future period do not incorporate factors accounting for this growth between the current and future periods.* In the approach presented here, we assume that there is an independent yield growth factor associated with technological change that is not accounted for in crop model simulations. However, if all technological change is accounted for in the crop model simulation methodology, then the growth factor Γ should be set equal to 1.

A5: *Area allocated to the crop is constant within the current and within the future time period (but not necessarily the same between the two periods).* This assumption is based on the premise that data on area variation over time are not available within the current period, and are not modeled for the future period; alternatively, the analyst can use year-specific data if such information is available.

2. Calculating TOA-MD Model Parameters

Matched Data

Step MA1: Calculate the relative yields r_j for each farm $j = 1,\ldots,J$ in the survey.

Step MA2: Survey data provide observations of $y_{1|k}$. Calculate system 1 variables for each farm in the survey data for the current period as:

$$\mu_{1j} = \beta_{yk} \cdot y_{1|k} \cdot \Gamma$$

$$R_{1j} = \phi_1 \cdot p_1 \cdot a_{1j} \cdot \mu_{1j},$$

$$G_{1j} = \beta_{ck} \cdot \Psi \cdot C_{1j}/R_{1j},$$

$$V_{1j} = R_{1j} - \beta_{ck} \cdot \Psi \cdot C_{1j}$$

Note that $\Gamma = 1$, $\phi_1 = 1$, $\Psi = 1$ **for Core Question 1**

Note: p_1 is a representative price, adjusted to the current period average as necessary. β_k is the normalization factor used to adjust observed yields in the data to the current period population average. The current period is defined as the five-year period centered as closely as possible on the year(s) of the economic survey data. Minor crops and livestock are not normalized.

Step MA3: calculate system 2 variables for each farm in the survey data for the future period:

$$\mu_{2j} = r_j \cdot \mu_{1j}$$

$$R_{2j} = \phi_2 \cdot p_2 \cdot a_{2j} \cdot \mu_{2j}$$

$$C_{2j} = G_{1j} \cdot R_{2j}$$

$$V_{2j} = R_{2j} - C_{2j} = (1 - G_{1j}) \cdot R_{2j}$$

Note that $\phi_2 = 1$ **for Question 1**

Step MA4: Using the data from MA2 and MA3, calculate the means for R_{1j}, C_{1j}, R_{2j} and C_{2j}, and the standard deviations of V_{1j} and V_{2j}, where the calculations for the future period made over all farms and future growing seasons.

Step MA5: Calculate RHO12 as the correlation between V_{1j} and V_{2j}.

Note: RHO12 may be over-estimated using these procedures due to the under-estimation of future yield variation by crop or livestock models. Therefore the upper bound on RHO12 is set at 0.95. That is, if the estimated value of RHO12 is greater than 0.95, the value of 0.95 should be used.

Unmatched Data, Time Averaged Method

As defined above, in the unmatched data situation, a distinct crop yield ***cannot*** be simulated for each survey farm; however, spatially and varying weather and soil data are available to run crop model simulations with representative management for the region. Thus, instead of simulating a relative yield r_j for each farm, we use the available data to simulate a distribution of relative yields for farms in the study region.

The basic idea behind the approach is to define statistical distributions for the variables of each system, and to use the available data to estimate the parameters of these distributions.

The key missing piece of information is the correlation between systems, which must be approximated using some assumptions. Thus, in implementing the unmatched case, subjecting the model to a sensitivity analysis of these assumptions is important.

For the un-matched case we use the following additional definitions and assumptions:

μ_h = mean of y_{hj}, h = 1,2

σ_h = standard deviation of y_{hj}, h = 1,2

$r = \mu_r + \sigma_r e_r$, $e_r \sim (0,1)$ = mean of r_j

$a_2 = \mu_a + \sigma_a e_a$, $e_a \sim (0,1)$

$G_2 = \mu_G + \sigma_G e_G$, $e_G \sim (0,1)$

A5 $e_r \sim$ iid(0,1) (r is independently distributed)

A6 $e_a \sim$ iid(0,1) (a_2 is independently distributed)

A7 $e_G \sim$ iid(0,1) (G_2 is independently distributed)

Step U1: same as step MA1

Step U2: same as step MA2

Step U3: calculate statistics for system 1 variables: μ_a, μ_r, μ_1, σ_a, σ_r, σ_1

Step U4: Use the statistics from Step U3 with the *TOA-MD Statistics Calculator* to calculate the system 2 statistics for the TOA-MD model. Note, this includes the value for the between-system correlation (RHO12). This estimate of the between-system correlation depends on the independence assumptions A5, A6 and A7. Therefore, it is wise to subject the model to sensitivity analysis around the value of RHO12 generated with this mode.

Multiple Activities

For systems with multiple activities, we apply the above calculations to each system. In addition, we need to estimate the within-system correlations between the returns to the activities. With matched data we can calculate the within-system correlations for system 2 the same way as for system 1 (i.e., by using the survey data to estimate the within-system average correlation between activities). For unmatched data, we typically assume that within-system correlations are the same for systems 1 and 2.

For trend calculations, yield trends for major crops from global models are used as the starting point, with adjustments to regional conditions as appropriate. Minor crop trends should be defined by the team based on the major crop trends. Livestock trends should be based on global model trends for milk and meat as appropriate, adjusted to regional conditions.

Appendix 3

Crop Model Simulations for Integrated Assessments: User's Guide

K. J. Boote, C. Porter, C. Villalobos, J. Hargreaves, J. Antle, R. Valdivia, and J. W. Jones

December 3, 2012

Introduction

This document describes AgMIP tools and procedures for using farm household survey data to create input files that are formatted for use in different crop models. It also describes the crop model output files that are needed for input to the TOA-MD economic model for integrated climate assessments. These files and procedures are provided for the "Matched Data" case, which means that a distinct crop yield can be simulated for each surveyed farm field, for each crop in the survey for which one or more crop models are available. In order to simulate each farm field that is in a survey, a minimum set of input variables is needed by crop models. Generally, farm survey data do not include all variables needed by crop models to simulate crop growth and yield. Thus, in order to simulate yields for the fields, assumptions have to be made about a number of input variables that are missing. Some models have used their own built-in default values for missing inputs. However, this is not an acceptable practice. It is highly important that the assumptions about missing input values are transparent to users, consistent across all models used in the integrated assessments, and clearly documented. Furthermore, users need to have the ability to set missing values that best represent the farming systems that are being analyzed, and these will vary across regions.

Data collected in farm surveys vary considerably from study to study. Here, we define the absolute minimum farm survey data necessary in order to approximately simulate each field's yield for the matched data case. We also define the minimum set of data needed to simulate crop growth and yield when the models are used to simulate water and N limited production. Because of the need to supplement farm field survey data with assumed values, two files are needed to provide all of the information needed to create crop model-ready input files: 1) the farm survey data, and 2) a corresponding file that contains the assumed variable values that are needed to quantify all required input variables that are not in the survey data. We describe these two files needed by AgMIP software to produce crop model-ready input files and give an example of each. In addition, we describe a third file needed for setting up multi-year runs (baseline, climate scenarios, and RAPs). We also describe the software that does the translations and the model output file that is needed by the TOA-MD model for the integrated assessment.

Managing and Documenting Crop Model Inputs

Table A3.1 presents file types that can be used to import data to the AgMIP data translation tools. Templates of each file type are provided for users to enter data observed at their research or survey sites. These templates contain headers which correspond to variables in

the ICASA Master Variable list for which precise definitions and units are listed. These definitions and units are replicated in the templates as comments to help guide the user to the correct form of the input data.

Raw survey data, measured at individual sites is stored in a Survey_Data_Import file. Invariably, some required crop model inputs are not measured and must be assumed. Some crop models have internal assumptions that provide missing inputs but these are "hidden" from users, they vary across models, and they are not likely to be relevant for all regions where the models will be applied. In addition, some computer simulations make use of observed management, soil, and climate, but modify some of these factors to evaluate climate variability effects at a location, to assess impacts of future climate, and to evaluate hypothetical management options. The "Data Overlay for Multimodel Export", or DOME, is a file type that is used by AgMIP tools to provide additional data used by each crop model to simulate crop growth and yield. Table A3.1 describes different types of DOME files currently implemented by AgMIP IT tools.

One purpose of a DOME file is to provide model input information that is not contained in farm surveys, yield trials, or even field experiments. For example, data collected in regional surveys usually do not have all inputs needed for crop model simulations. The Field_Overlay file is used to fill in the needed inputs that are missing so that all of the models make use of the same regional or site-specific assumptions. This concept ensures the integrity of observed values, clearly documenting assumptions made for simulation analyses, and it ensures consistency across crop models for multi-model applications.

A second type of DOME, the Seasonal_Strategy file, is used to provide information needed to create synthetic simulation experiments for multiple seasons of weather data. These files provide information for controlling simulations for multiple years, for example, and/or management practices, cultivars, and other inputs that define a particular scenario that is to be simulated. These files can provide information to set up baseline management and climate simulations over multiple years, or they can be used to set up management adaptation options that may be derived from the Representative Agricultural Pathways (RAPs) analyses. In these cases, the soil, climate, and management regimens in Seasonal_Analysis DOME files would override existing recorded management and replace those data with the prescribed regimen.

AgMIP data translation tools include a utility that will allow crop modelers to match the survey data with chosen DOME files that describe missing inputs for management practices and soil conditions for a particular analysis. The Field_Overlay and Seasonal_Strategy DOME files are combined with archived survey data (Survey_Data_Import files) and used by the data translators to produce model-ready crop model input files for multiple crop models.

Data Requirements for Simulating Each Surveyed Field (Matched Case)

Microsoft Excel files are used to collate the data described in Table A3.1. The Excel files are exported by users into comma-delimited files (*.csv files). Software was developed to read and interpret these *.csv data files containing the Survey_Data_Import and Field_Overlay data.

The Survey_Data_Import file must be created from the field survey information, with one line per farm-field that was sampled in the survey. Table A3.2 lists the data that are required in this file. Generally, household survey information includes crop yield, some management information, and economic data on a per farm-field basis, which may be in any format (e.g., Excel, ASCII, or print form). If the data are not in correct units or definitions (dry matter or ear versus grain), conversions are needed prior to entering data into the Survey_Data_Import spreadsheet. Table A3.3 lists an absolute minimum set of observations from field surveys; unless these data are available or can be estimated from the raw survey data, the crop models cannot be used to simulate matched field yields for the TOA-MD economic model analyses. Typically, users can use the field LAT/LONG (preferred) or the village location for use in interpolating climate data for the site and for selecting an appropriate set of soil properties.

An example Survey_Data_Import file is provided with this document that contains the field survey data along with soil and climate data for the fields in the format needed by AgMIP software. Each tab (worksheet) in the file must be saved as a separate comma-delimited (*.csv) file.

Soil and climate data are typically not collected in farm surveys, so these data must be provided by users who are preparing the survey Excel data file for use by AgMIP software. Climate data may be provided in *.AgMIP format (the standard format used by the AgMIP climate team) as an alternative to comma-delimited (*.csv) format.

A second set of Excel files, the Field_Overlay DOME files, contain all assumptions about crop management and initial conditions that are rarely or never measured in the household surveys. There may be up to one Field_Overlay file per field if fields are highly different and need different assumptions about required inputs that were not measured. [*These initial conditions and management assumptions are not trivial and can make a large difference in simulated yield. See later discussion describing how Agronomists and experts in the region need to be consulted in order to create this file.*] Table A3.4 provides a list of the currently-defined minimum management and initial soil condition information needed by crop models (*that are likely not provided in the household survey*). These data are entered into the Field_Overlay file for use by AgMIP software to fill data not available in the farm survey data. The overlay files also document explicit assumptions made and used consistently across all crop models for the simulations. The Field_Overlay file along with the corresponding Survey_Data_Import Excel file provide all of the input data currently needed to run crop models for the matched field survey of observed yields. Later, we will describe an additional Seasonal_Strategy.xlsx type of DOME file that will be additionally needed to run multiple year baseline and multiple year climate scenarios as well as RAPs.

Software for Producing Crop Model Input Files

QuadUI is a desktop utility that reads survey and DOME data and translates to model-ready format. This software reads all field information contained in the matched Survey_Data_Import file and the associated Field_Overlay files and creates DSSAT and APSIM model input files. Translators for other models are being integrated into QuadUI as they are developed by the various crop modeling teams.

Crop Model Outputs for Use by the TOA-MD Model

Outputs from the crop models are then arranged into the AgMIP Crop Model Output file (ACMO.csv) for use as input to the TOA-MD model. ACMOUI is a desktop utility that will generate the ACMO harmonized crop modeling output file from the various models. This file contains metadata which fully describes the crop model simulation linking the model outputs to the ACE and DOME data.

Procedures for Creating Crop Model-Ready Input Files for Survey Fields

Step 1. Gather, assemble and enter data (survey and expert)

- Download data translation tools from http://tools.agmip.org/
  - QuadUI – desktop application for data translation
  - ADA – converts from Excel to csv format for import to QuadUI
  - ACMO_UI – converts model output to ACMO format
  - Sample spreadsheet templates for survey data and DOME data ICASA Variables List– list of variables to extend the survey data template, if needed (http://tinyurl.com/ICASA-MVL)
- Using one of the survey data templates, enter the appropriate following data by either: 1) cut-and-paste, or 2) direct entry. The entry is on a "per-farm-field" basis, one line per site. If you have additional field-measured variables that are not included in the template, it is possible to extend the file to include your variables. The ICASA Variables list shows all of the possible variables that can be used to define site data. Additional columns can be added to the survey data import template for those data.
- If some data are missing, one or more Field Overlay templates should be used to FILL in the missing data (examples are dates of N fertilization or manure application). There can be multiple field overlays, if soils and soil initial conditions vary across farms. The Field_Overlay ID is specified per site in the survey data import file. Required minimum data include:
  - Field/Farm Name
  - Latitude and longitude of farm (or give nearest village name)
  - Weather station identifier (connects to climate files)
  - Soil identifier (name connecting to soil files)
  - Field_Overlay identifier (name connecting to all the unknown management assumption information for a given Field)
  - Crop (maize, wheat, etc.)
  - Sowing date
  - Plant population (plants per m2)
  - N fertilization (amount, kg N/ha and date of application)
  - Manure or organic matter applied (amount, kg/ha dry matter, and date)
  - Irrigation (yes or no)
  - Harvest date (desired, but not crucial)
  - Harvested yield (kg/ha dry matter)
  - Harvested byproduct (non-grain) removed by farmer (desired, not crucial)
- Visit with Soil Scientist experts from the region: Find the appropriate soil for each farm (linking to latitude-longitude or village information), and enter the soils information by soil layer in the soil tab in the Survey_Data_Import file. The soil name is also listed in the field section of the Survey_Data_Import file.

- There will be one or more Field_Overlay sheet, in which you will enter expert knowledge of Agronomists and Soil Scientists to define all the missing information that is not available in the household survey data, defining probable initial conditions related to initial soil water, initial soil mineral N (NO3 & NH4), soil organic carbon, prior crop residue, prior root residue, shape of initial mineral N, shape of SOC, shape of inert SOC, and shape of probable rooting profile. Do not attempt to simulate without a field overlay file, as data will inevitably be missing and model defaults incorrect.
    - Field_Overlay files will tend to be soil-related for initial conditions for water, mineral N, SOC, SOM, residue, rooting shape where soils are different.
    - Field_Overlay files may also be sowing-related (plant population) or fertility management-related (fertilizer/manure).

Step 2. Save Survey_Data_Import and Field_Overlay Data to csv format

- Using the ADA utility, save Survey_Data_Import sheets in comma delimited (csv) format, one for field, one for soil, and one for each climate file, zipped into a single archive. Caution: Do not open the *.csv files again with Excel, as they ARE NOT true spreadsheets and do not correctly convert back into Excel files; the date format can revert to a machine-dependent format.
- Using the ADA utility, save the Field_Overlay spreadsheets in comma delimited (csv) format, zipped into a single archive.

Step 3. Translate data files to model-ready formats

- Run QuadUI by double-clicking on the QuadUI.bat file. Respond to the on-screen requests for location of zipped Survey csv files and zipped Field_Overlay csv files, as well as the placement for the output crop model files. If you are not successful, view the QuadUI log report in the QuadUI folder.
- Your ending point will be files for running crop models, i.e., Files X, A, SOIL.SOL, *.CUL, *.WTH for DSSAT, and similar files for APSIM or other crop models. In the case of DSSAT or APSIM, simulations can be run by double-clicking the DOS batch file that was created with the translations.

Step 4. Check and correct missing/invalid model input data and run simulations

- Run the crop model. With APSIM, load the simulation and view the log. With DSSAT, look at the Error.OUT and the Warning.OUT files. These files will tell you if the climate file or cultivar were not found, or if some variables such as sowing date or plant population were missing. With APSIM, after the issues in the LOG are dealt with, run the simulation. APSIM produces summary files (*.sum) which are a log of significant events and warnings/fatal errors. The summary files need to be checked for errors which may need to be corrected, otherwise the error in simulated yields may be significant. If there are failures, go back to the Survey_Data_Import and Field_Overlay DOME files. Common errors include:
    - If plant population (or other) was not in the Survey_Data_Import file, and is not found, then you did not connect the Field_Overlay file correctly.
    - Field_Overlay name was not entered in the survey template exactly as in the Field_Overlay file. In this case, no Field_Overlay data were found.
- Evaluate the outputs. In DSSAT, look at the Evaluate.Out file which will list both the simulated and the observed yield. In APSIM, there is a single line output for each simulation. The APSIM-simulated yield values will need to be aggregated (assembled) into one file. The observed yields are in the Survey_Data_Import file and will need to be matched per field.

Step 5. Create AgMIP Crop Model Output (ACMO) File for use by Economic Team Members

The ACMO file is partially created by QuadUI at translation time in the form of the ACMO_meta.dat file which contains metadata in one line per field so that all of the information used to simulate results for the fields is documented in a way that users could reproduce the results. Running ACMOUI, a desktop utility, will complete the ACMO file with the selected crop model simulated outputs.

Note that the ACMO files contain raw simulated results for each field, not aggregated or adjusted in any way. This will ensure integrity of both inputs and model outputs. Table A3.5 lists all of the variables that ACMO contains along with information on variables created by QuadUI and those that must be added by crop modelers.

Create Crop Model-Ready Input Files for Simulating Multi-Year Baseline, Climate, and RAPs Scenarios (Using Strategy_Analysis files)

A Seasonal_Strategy type of DOME file will be created to assist multi-year simulations for baseline and climate scenarios, both with and without RAPs. The starting point will be the Survey_Data_Import and the Field_Overlay files that were already created for the surveyed fields. In this case, the Survey_Data_Import file, in addition to having a Field_Overlay ID per field, will also have a Seasonal_Strategy ID (possibly just one for all farms in the survey). Examples of what is in that file include:

- For Baseline Multi-Year: auto-sowing rules
- For Future Climate Scenarios: auto-sowing rules, plus link to new weather station IDs
- Translating RAPS into management using the Seasonal Strategy (RAPs can led to improved crop and soil management practices including improved genetic technology). Specifics include:
    - Auto-sowing, possibly modified for earlier/shorter sowing window because of better machinery
    - Weather station ID
    - changed plant population,
    - improved or alternative crop cultivar,
    - changed N fertilization,
    - increased prior root and surface residue (because of better fertilization-population-cultivar)
    - other adaptation strategies, as needed

To run a Seasonal Strategy, repeat all of the steps for baseline analysis, using the Survey_Data_Import and Field_Overlay files, but now the Seasonal_Strategy DOME files are also prepared using the spreadsheet templates. Each of the three sets of files (Survey_Data_Import, Field_Overlay, and Seasonal_Strategy) should be compressed into separate zip files for import to QuadUI.

Notes on Use of Field_Overlay Files

- Function and Purpose of multiple Field_Overlay files

- Fill in data that crop models need that are almost never available in household survey, such as initial soil water, initial soil nitrate and ammonium, soil organic carbon pools (SOM3 for DSSAT-CENTURY, and inert SOC for APSIM), and rooting depth (see Table A3.4). The shape of these listed variables by soil depth is also generally missing.
- Fill in needed data missing from household survey, such as root residue from prior crop, surface residue from prior crop, sowing date, sowing depth, plant population, amounts and dates of fertilizer or manure applied.
- Link to cultivar ID and model specific cultivar ID
- It can be used to set automatic sowing rules for each field in the survey, if planting dates were not recorded.

- Where to get Field_Overlay information? First, DO NOT use crop model defaults, as the model defaults are wrong and differ among crop models. Often defaults use zero or unity values when not appropriate and these are not region-specific. Secondly, this must be done in close collaboration with local agronomists and soil scientists.
  - Agronomists and soil scientists in the region who know production practices for the crop and region in question. Although they may not give specific values for the needed inputs, they will likely provide very useful ranges of likely missing input information.
  - Soil survey information (linking to latitude-longitude coordinates for field).
  - Country-wide statistics (amount of N fertilization per hectare), but this is not region- or crop-specific.
  - Pre-simulations with crop models with correct soil organic carbon and SOM3 (or inert SOC) pools, for setting SOM3 and inert SOC to give the low non-fertilized non-legume yields for the region (requires knowledge of unfertilized yield for region). Take the mineral nitrate and ammonium from the values simulated at the end of the "prior" season.
  - Make sure that the assumed values that you use in the Field_Overlay file are consistent with all of the expert knowledge and soil survey information, and document how these values were developed.
- Principles for use of Field_Overlay files:
  - First obtain knowledge from agronomists, soil scientists, and soil surveys.
  - Do not use model defaults for missing information
  - Then use QUADUI with Survey_Data_Import and multiple Field_Overlay files, to create model-ready files for simulation.
  - Simulate farmer fields (n = 50 to 150)

Summary of Simulation Runs Needed for Integrated Assessments

Crop modeling teams need make several separate sets of simulation runs and prepare several ACMO files for the integrated assessments. The ACMO will be provided to the Economic modelers for use in the TOA-MD analyses. Specifically, the following set of runs will need to be made, each with its corresponding ACMO file:

1. Matched simulations, with observed inputs and raw crop model results (not bias-corrected). This set of runs will require the Survey_Data_Import field survey file along with the Field_Overlay file.
2. Simulation Set #1. Current system simulation results, multiple years (e.g., 30 years), which means current climate and current management conditions. This set of runs will require the same two files above in addition to a Seasonal_Strategy file that will set up the multi-year simulations.
3. Simulation Set #2. Climate change simulated results, multiple years (e.g., 30) using **current** management with future climate conditions. This allows paired climate

change impact assessments. This set of runs will also require the same two files above in addition to a Seasonal_Strategy file that will set up the multi-year simulations, this time using a future climate scenario.

4. Simulation Set #3. Climate change simulated results, multiple years (e.g., 30) using **adaption** management with future climate conditions. This allows paired climate change impact assessments. This set of runs will also require the same two files above in addition to a Seasonal_Strategy file that will set up the multi-year simulations, this time using a future climate scenario. Adaptation scenarios include improved cultivars, different fertilization, and altered sowing dates, consistent with RAPs.
5. Archive model simulations (inputs, management, outputs, soil, climate, cultivar coefficients, simulated outputs) by placing them in the ACE, DOME and ACMO databases.
6. Document simulations with explanatory text and appropriate tables and figures showing the yield distributions and analyses of interannual and spatial variations. Create maps and summary statistics e.g., spatial distribution of climate, soils, management, and yields illustrated in GIS mapping methods.

Guidelines for Analysis of Crop Model Simulated Outputs for Matched Fields

Crop modelers should analyze model outputs prior to use of the data in the regional economic analysis. This is very important to ensure quality control of the process and that crop modelers are able to understand the variability in results. It is also important that crop modelers will be able to conclude that simulated yields are reasonable representations of water and nitrogen-limited yields, recognizing that other factors, such as other soil nutrients and pests, are likely to contribute to actual yields in a region and that these factors could vary considerably over space and time. We have provided suggestions for analyzing crop model outputs, including computation of means, distribution of observed and simulated yields, computation of mean bias between observed and simulated yields, and analysis of outliers.

- Evaluate Simulated and Observed Yields for Mean, Bias, and Distribution
- Place simulated yield and observed yields into a spreadsheet, computing means and standard deviation. Compute bias of the mean observed yield divided by mean simulated yield. We do not recommend computing bias of individual fields if there are any zero simulated yield values, as that will give error.
- Rank the observed yields and simulated yields from high to low and compute cumulative probability distributions of observed and simulated yields.
- Attempt to identify outliers and reasons for high mean bias as well as large differences between cumulative distributions of simulated and observed yields. These analyses may help crop modelers critically evaluate some of the input assumptions in the Field_Overlay file, for example, relative to the information from regional agronomists and other sources that were used to set the values. If there is a large bias, it would be good to review the inputs and results with agronomists. We do not recommend any type of calibration for reducing the bias; this is intended to improve the reliability of the process and results. These analyses may be useful in reporting and in publishing crop model results; only the final raw field-by-field simulated yields will be used in the ACMO file. Some ideas to consider as you analyze results are:
    - If bias (observed over simulated) is dramatically different from 1.00 (for example 0.5 or 1.5), there may be problems in Field_Overlay assumptions.

Bias is driven by the mean simulated and observed yields. For example, a high bias of 1.5 or more could indicate that soil N availability (SOM3, initial nitrate, initial ammonium) or soil water availability (initial or capacity) is not high enough. A low bias of 0.5 (model simulates too high) could indicate too much soil N availability or too much water availability.

- The full range of the cumulative distribution is driven not just by the management and climate, but also by the extent of range of initial nitrate, ammonium, SOC, SOM, DUL-LL, and initial soil water found across all the farms. If that range of inputs is small (because of inadequate Field_Overlay entry), then the simulated distribution of yields could be insufficient.
- Strong left tails in simulated distribution (or observed) are indicators of crop failures (zero and very low yields). If left tails is too strong in simulated, then you may need to increase initial soil water content to reduce the instance of simulated germination failures, or increase rooting depth or DUL-LL to minimize crop failures during reproductive growth.
- Strong right tails in simulated or observed distributions are indicators of high yields. If simulated right tails are too strong (or too little) where the water and N stresses are minimum, one can make the case that genetic yield potential of the cultivar is too high (or too low).
- These "indicator" problems are given, not for the purpose of re-calibrating the crop models to fit the distribution, but for the purpose of highlighting the need for obtaining correct Field_Overlay information in the first place.

Table A3.1. Description of data files used by AgMIP IT tools to create multiple crop model input files.

Type of File	Name	Description	File Type(s)
Raw data	Survey_Data_Import	A file used to provide observed field survey data for use in creating multiple model inputs	Excel Spreadsheet, one line per field, which is exported to a comma-delimited (*.csv) file for import
DOME	Field_Overlay	Used to provide missing inputs needed by models that are not in the observed field survey data	Excel Spreadsheet, which is exported to a comma-delimited (*.csv) file for import. File name is used to link this file to each field in the Survey_Data_Import file
DOME	Seasonal_Strategy	Used to set conditions for multi-year model simulation of alternative management practices, soils, with multiple historical or future years of climate data.	Excel spreadsheet, which can be used with observed field data and associated field data overlay files for studying crop responses to seasonal climate variability (same initial conditions each season). Exported to comma-delimited (*.csv) format for import.
DOME	Rotation_Strategy	Used to set conditions for multi-year model simulation of crop rotations, having just one set of initial conditions at year 1	[not yet implemented]
ACMO	AgMIP Crop Model Output file	These files contain a summary of crop model output data and document all of the inputs used by crop models to simulate those outputs. These files are used by TOA-MD economic model teams as input to their analyses. It also includes all metadata describing the field soil, climate scenario, and management such that simulation can be repeated.	Comma delimited file which contains harmonized crop model simulation outputs for input to the regional and global economic models. The file helps ensure that outputs are consistent between models and are fully linked to the data sources.

Table A3.2. List of variables in the household survey FIELD data needed to run crop models. These data are in the Survey_Data_Import.xlsx EXCEL file. Note that some of these data may not have been collected in the survey but are provided later by those who are preparing the data for translation by AgMIP software tools into model-specific input files needed to run each crop model.

Data Type	Units	Variable Name
Field/Farm name		EXNAME
Field overlay name(s)		FIELD_OVERLAY
Seasonal strategy name(s)		SEASONAL_STRATEGY
Latitude	dec. degrees	FL_LAT
Longitude	dec. degrees	FL_LONG
Weather station identifier to link to site information		WST_ID
Soil profile identifier		SOIL_ID
Planting date	yyyy-mm-dd	PDATE
Crop ID (see list of codes above)	code	CRID
Total seasonal N applied	kg[N]/ha	FEN_TOT
Manure/Organic matter applied	kg[DM]/ha	OMAMT
Harvest date	yyyy-mm-dd	HDATE
Harvest yield (dry wt)	kg[dry]/ha	HWAH
By-product removed at harvest as dry wt	kg[dry]/ha	BWAH
Indicates whether the field has been irrigated	Y or N	IRRIG
Notes (as desired, optional)		TR_NOTES

Table A3.3. List of observations that are considered absolute minimum in order to simulate each field in the survey using management, climate, and soil information for the field, the "matched data" case.

1. Village name for climate data interpolation, which will almost always have to be done).
2. Farm/field name (This plus village name provides the unique field name for the simulation and location is used to identify a suitable soil to obtain soil inputs needed for the model.
3. Crop species
4. Sowing date (yyyy-mm-dd).
5. Mineral N fertilizer amount used (elemental N applied per ha, or at least categories that can be consistently interpreted to estimate amounts, such as none, low, medium, and high)
6. Farmyard manure or organic matter applied. If not given, we would assume that it is zero.
7. Whether irrigated or not. Probably, this is rare in most of our AgMIP SSA and SA projects, except for rice. Also could include total irrigation for the season in mm (IRR_TOT).
8. Grain yield (dry weight per ha, or otherwise indicate basis and units for yield in survey data.

Table A3.4. A list of the minimum management and initial soil condition information needed by crop models that is probably ***not*** provided by household yield survey. **indicates data hopefully provided from survey.

1. Cultivar ID (link to model-specific cultivar)
2. Sowing date (yyyy-mm-dd)**
3. Sowing depth (cm),
4. Plant population (plants/m2) **
5. Mineral N fertilizer amount used (kg elemental N applied per ha), dates of application (yyyy-mm-dd or days after sowing), percentages for split amounts? **
6. Farmyard manure or organic matter applied (kg DM per ha) and dates of application (yyyy-mm-dd or days after sowing).**
7. Whether irrigated or not.**
8. Root residue from prior crop (kg/ha)
9. Surface residue from prior crop (kg/ha)
10. Maximum rooting depth (and shape relative to 1.0 in topsoil)
11. Initial soil water (zero to 100% of available) (for each layer, or shape?)
12. Initial soil nitrate and ammonium (for each layer or shape in profile if kg N/ha total?)
13. Soil organic carbon pools (fraction SOM3 for DSSAT-CENTURY, or fraction inert SOC for APSIM), by each layer, or shape.

Table A3.5. List of variables contained in the ACMO file for documenting crop model runs and for use by economic modelers in the TOA-MD analyses. Also the table shows which variables are created automatically by the AgMIP IT Tool, QuadUI and which must be added by crop modelers.

Variable Name	Definition	Units
Metadata or Crop Model Input summary data (provided by QuadUI)		
EID	Experiment ID	
SUITE_ID	Suite identification, for linking groups of sites or experiments	
RUN#	Simulation order	
FIELD_OVERLAY	Name of field overlay(s)	
SEASONAL_STRATEGY	Name of seasonal strategy(ies)	
EXNAME	Name of experiment, field test or survey	
TRT_NAME	Name of treatment	
CLIM_ID	4-character Climate ID code	
CLIM_REP	Climate replication number for multiple realizations of climate data	
REG_ID	Region ID	
STRATUM	Regional stratum identification number	
RAP_ID	RAP ID	
MAN_ID	Management regimen ID, for multiple management regimens per RAP	
INSTITUTION	Names of institutions involved in collection of field or survey data	
ROTATION	Crop rotation indicator (=1 to indicate that this is a continuous, multi-year simulation, =0 for single year	
WSTA_ID	Weather station ID	
SOIL_ID	Soil ID	
FL_LAT	Site Latitude	decimal degrees
FL_LONG	Site Longitude	decimal degrees
CRID_text	Crop type (common name)	
CUL_ID	Crop model-specific cultivar ID	
CUL_NAME	Cultivar name	
SDAT	Start of simulation date	yyyy-mm-dd
PDATE	Planting date	yyyy-mm-dd
HWAH	Observed harvested yield, dry weight	kg/ha
CWAH	Observed total above-ground biomass at harvest	kg/ha
HDATE	Observed harvest date	yyyy-mm-dd
IR#C	Total number of irrigation events	
IR_TOT	Total amount of irrigation	mm
IROP_text	Type of irrigation application	
FE_#	Total number of fertilizer applications	
FEN_TOT	Total N applied	kg[N]/ha
FEP_TOT	Total P applied	kg[P]/ha

FEK_TOT	Total K applied	kg[K]/ha
OM_TOT	Manure and applied oganic matter	kg/ha
TI_#	Total number of tillage applications	
TIIMP_text	Tillage type (hand, animal or mechanized)	
Crop model simulation output data (provided by the crop modeler)		
CROP_MODEL	Short name of crop model used for simulations (e.g., DSSAT, APSIM, Aquacrop, STICS, etc.)	
MODEL_VER	Model name and version number of the crop model used to generate simulated outputs	
HWAH_S	Simulated harvest yield, dry matter	kg/ha
CWAH_S	Simulated above-ground biomass at harvest, dry matter	kg/ha
ADAT_S	Simulated anthesis date	yyyy-mm-dd
MDAT_S	Simulated maturity date	yyyy-mm-dd
HADAT_S	Simulated harvest date	yyyy-mm-dd
LAIX_S	Simulated leaf area index, maximum	m2/m2
PRCP_S	Total precipitation from planting to harvest	mm
ETCP_S	Simulated evapotranspiration, planting to harvest	mm
NUCM_S	Simulated N uptake during season	kg/ha
NLCM_S	Simulated N leached up to harvest maturity	kg/ha

Appendix 2

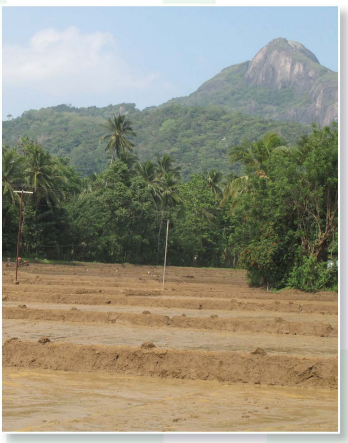
This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

Guide for Running AgMIP Climate Scenario Generation Tools with R

in Windows

Version 2.3



Version 2.3
Updated Oct. 25th, 2013

Guide for Running AgMIP Climate Scenario Generation Tools with R in Windows

This Guide explains how to create climate series and climate change scenarios by using the AgMIP Climate team's methodology as outlined in the AgMIP Guide for Regional Integrated Assessment: Handbook of Methods and Procedures (available for download at www.agmip.org)

Details how to:

- install R and the required packages to run the AgMIP Climate Scenario Generation scripts
- create climate scenarios from CMIP5 GCMs using a 30-year baseline daily weather dataset

The Guide also outlines a workflow that can be modified for application to your own climate data.

This Guide and workflow are under continuous development and we expect to add new capabilities and sections in future versions. The methods and scenarios here are intended for AgMIP research and may not be suitable for other applications. Please contact Nicholas Hudson (nih2106@columbia.edu) if you have any questions or comments.

By Nicholas Hudson (nih2106@columbia.edu), CCSR | Columbia University
and Alex Ruane (alexander.c.ruane@nasa.gov), NASA Goddard Institute for Space Studies
With special thanks to Yunchul Jung (University of Florida) and Sonali McDermid (NASA GISS)

Contents

★Background 3
Installation 4
Download and Install R 5
Download and Install Packages 6
★Downloading AgMIP Climate Scenario Generation Scripts and Data 10
Creating folders for R scripts and input data 10
★Downloading R scripts and data from WebDrive 11
★Creating baseline .AgMIP files with "AgMIP Excel File Template_v2.0.xls" 14
★Opening "AgMIP Excel File Template.xls" 14
Creating baseline .AgMIP files with the enabled macro 15
Creating baseline .AgMIP files without the enabled macro 17
★Running AgMIP Climate Scenario Generation scripts 19
★Explanation of input variables to be changed in the run scripts 19
Modifying variables in the run scripts 28
Sourcing the run scripts 32
Explanation of output files 33
Suggested workflows for the run scripts 37
run_agmip_farmclimate.R 38
run_agmip_simple_delta.R 39
run_agmip_simple_mandv.R 41
run_agmip_simple2full.R 43
Creating "full" files from "run_agmip_simple_delta.R" outputs 43
Creating "full" files from "run_agmip_simple_mandv.R" outputs 44
Next Steps… 46
Appendix 1: Creating .AgMIP files in Excel 47
Appendix 2: Example file for "agmip_farmclimate.R" 49
Appendix 3: Example file for "agmip_simple_delta.R" and "agmip_simple2full.R" 50

★Background

Version 2.3 of the Guide for Running AgMIP Climate Scenario Generation Tools with R provides updated links for downloading the input data and AgMIP Climate Scenario Generation scripts for R. Version 2.3 also corresponds with the updated version of the script "agmip_farmclimate.R" that was available with version 2.1.

The updated version of "agmip_farmclimate.R" includes a correction to handle negative vapor pressure (Vprs) values and NaN dew point temperature (Dewp) values as well as to correct NaNs created when calculating the change factor for precipitation (Rain). If you have encountered any of these errors when running "**run_agmip_farmclimate.R**", we recommend that you rerun "**run_agmip_farmclimate.R**" with the updated version of "agmip_farmclimate.R".

If you have not encountered these errors you do not need to rerun "**run_agmip_farmclimate.R**", but we highly recommend that you use the updated version of "agmip_farmclimate.R" for future analysis.

The updated version of "agmip_farmclimate.R" can be downloaded from the links provided in the section **Downloading R scripts and data from WebDrive**.

New sections or sections that have been substantially updated are marked with green stars (★). These stars have not been updated and reflect changes that were made for version 2.1.

The only difference of version 2.3 from versions 2.1 and 2.2 is that version 2.3 contains updated WebDrive links for downloading the necessary scripts and minor adjustments to "agmip_simple_delta.R" and "agmip_simple_mandv.R" to ensure that Tmax > Tmin in the generated climate change scenarios.

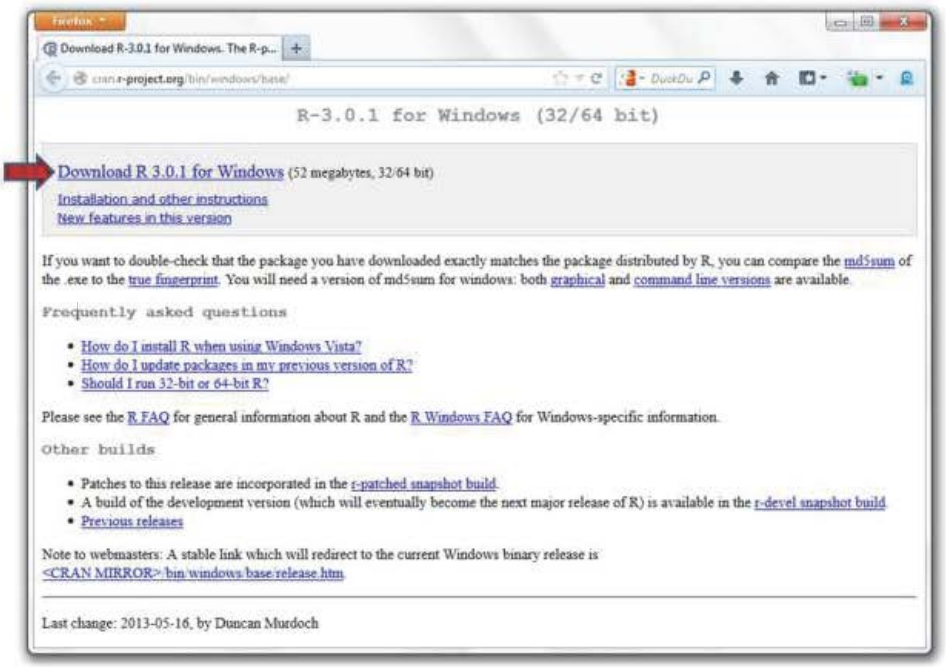
Installation

This section explains how to install R and the packages necessary to run the climate scripts.

R is a free environment that can be used for statistical analysis and graphic development. To run the scripts properly, packages are required to add functionality to R. These packages are free, easy to download, and importantly ***must be loaded, but not reinstalled, every time you begin a new R session***. The AgMIP Climate Scenario Generation scripts that are described in this Guide have been designed to load the required packages automatically as long as the packages have been properly installed.

Download and Install R

Download the most recent version of R from <http://cran.r-project.org/bin/windows/base/>. The image below shows a screenshot from the provided link to the R website. As you can see in the below image, the most recent version of R is 3.0.1 (as of the publication of this Guide). If there is a more recent version of R, you should download that version. To download the installation file in your web browser, click on the link indicated by the red arrow. Run the downloaded .exe file and follow the steps of the installation wizard. After the installation is complete, open R.



Note: The R website provides a lot of helpful information if you are experiencing any difficulties downloading or installing R onto your computer. Also, there are versions of R available for Mac OS <http://cran.r-project.org/bin/macosx/> and Linux <http://cran.r-project.org/bin/linux/>. Again, the R website is very useful so if you are installing R on either of these platforms and are experiencing any difficulties, your questions may be answered by information provided by this website.

Installation - 6

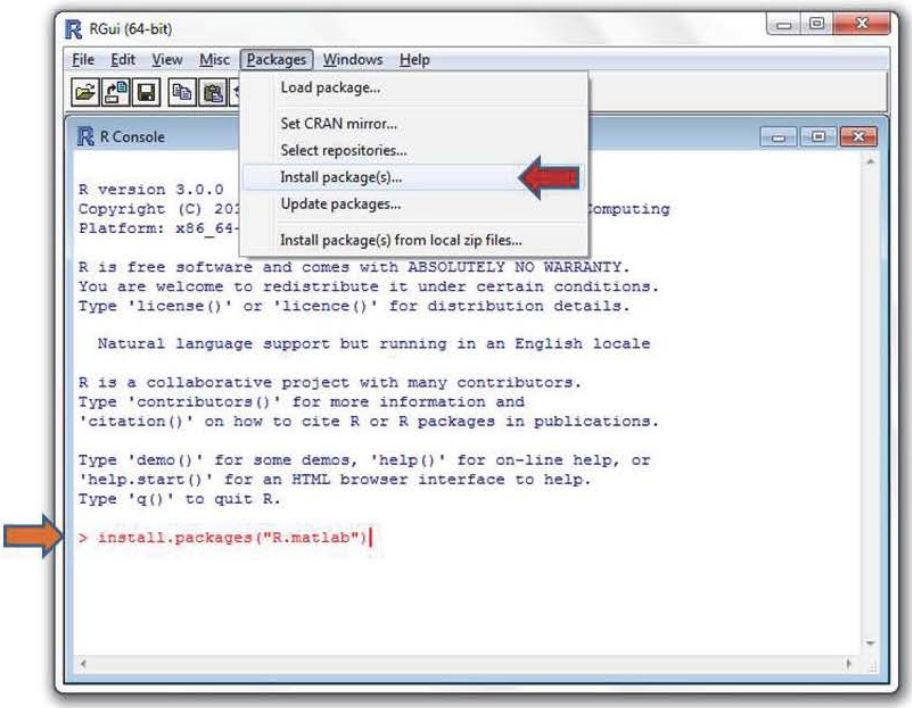
Download and Install Packages

1. After installing R onto your computer, you will need to install the "R.matlab", "R.utils", and "MASS" packages. Let's start with the "R.matlab" package. You can perform this action by either

- Selecting R: Packages-> Install package(s)… from the menu bar (shown by the red arrow below) or by
- Typing the command

```
install.packages("R.matlab")
```

into R Console (the orange arrow below).



Installation - 7

After selecting the nearest CRAN mirror, R will install the selected package "R.matlab" as well as the dependent packages "R.oo" and "R.methodsS3" to your package library. Occasionally the closest mirror does not work. If this is the case, simply try a different location. A successful install will display the following message in R Console:

```
package 'R.oo' successfully unpacked and MD5 sums checked
package 'R.methodsS3' successfully unpacked and MD5 sums checked
package 'R.matlab' successfully unpacked and MD5 sums checked
```

IMPORTANT: The next step, Step 2, is crucial for the installed packages to run correctly. ***The packages must be loaded, but not reinstalled, every time you begin a new R session to perform the operations required by the provided climate scenario scripts.*** However, the provided scripts described in this Guide automatically load the necessary packages with the 3 line code shown below:

```
library <- c("R.matlab","R.utils")
lapply(library, require, character.only = T)
rm(library)
```

Thus, if you will only be running the provided climate scenario scripts, you can skip Step 2 and proceed to Step 3. If you are designing your own scripts and would like to retain the functionality of the provided scripts you will either need to incorporate the three line code above or follow Step 2 to load the packages.

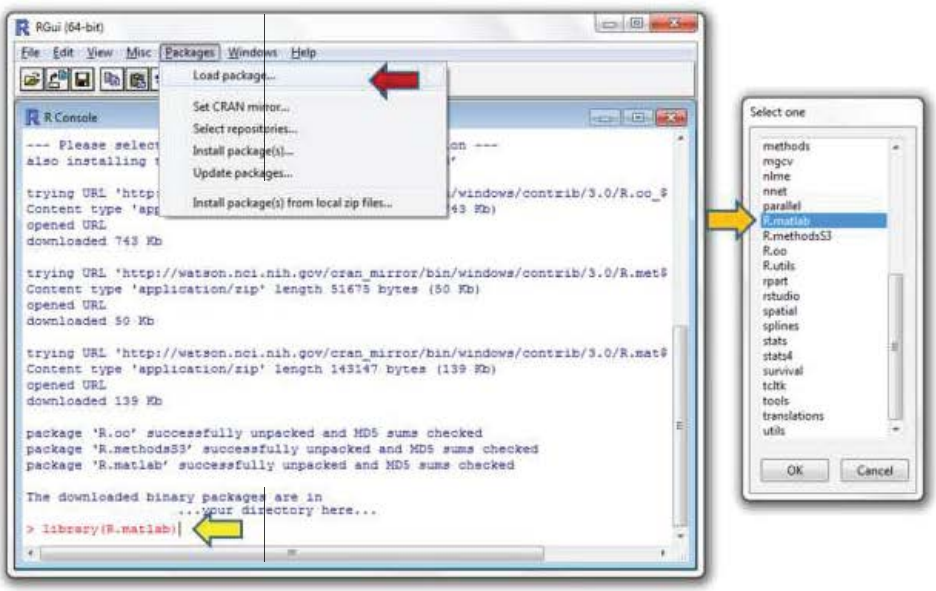
Installation - 8

2. Load "R.matlab" package. You can perform this action in one of two ways.

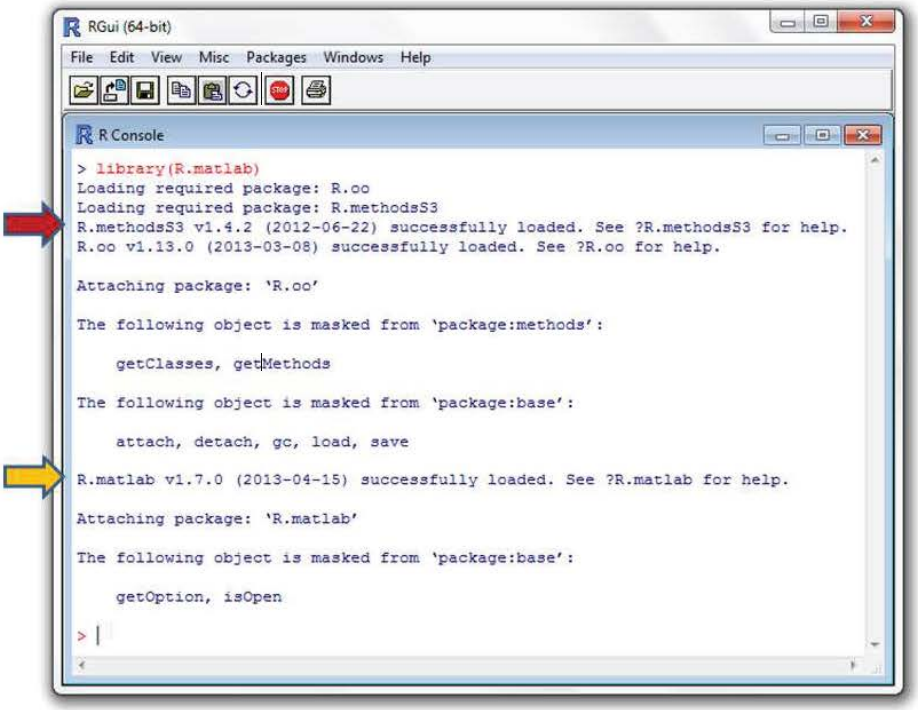
- **You can select R: Packages-> Load package… from the menu bar (shown by the red arrow below), which brings up a pop-up box titled "Select one." Choose "R.matlab" as indicated by the orange arrow.**
- **Alternatively, you can type the command**

```
library(R.matlab)
```

into R Console as is indicated by the yellow arrow below.



When loading R.matlab, R will automatically load the dependencies, R.oo and R.methodsS3. R Console's output will inform you if all three packages were successfully loaded. The red arrow below points to the lines indicating "R.oo" and "R.methodsS3" were successfully loaded, while the orange arrow points to the "R.matlab" line.



3. Repeat steps 1 and 2 (pages 6-8) to install and load the packages "R.utils" and "MASS".

IMPORTANT: The "MASS" package will be used by "agmip_simple_mandv.R" and has been added to the list of required packages for Version 2.0 of the Guide. If you are intending to run the script "run_agmip_simple_mandv.R", you will have to install the "MASS" package. Otherwise it is not necessary to install this package.

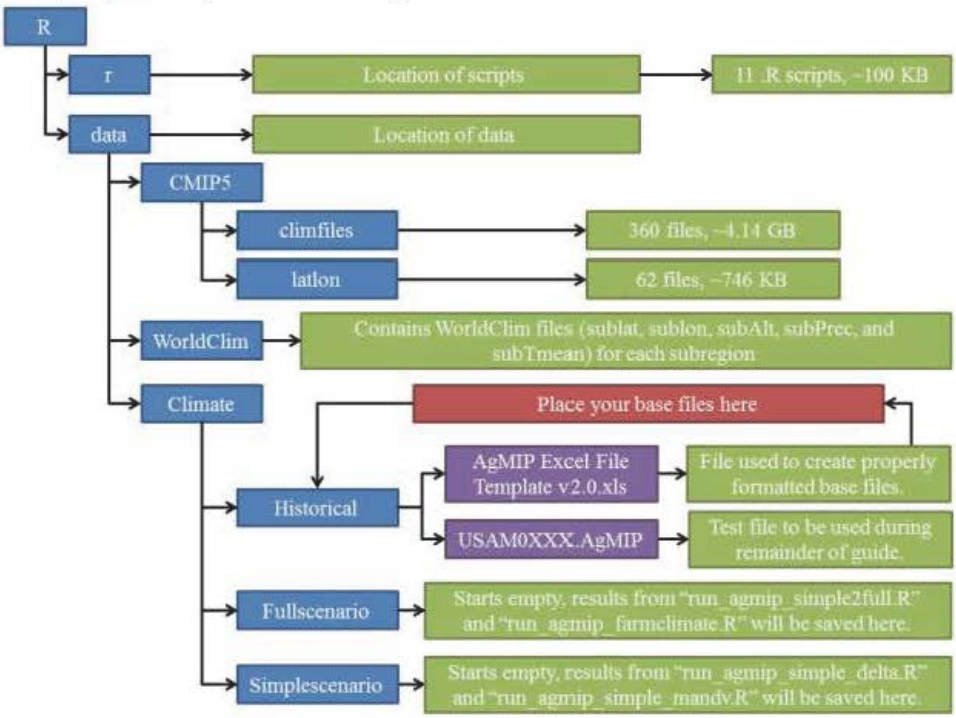
★Downloading AgMIP Climate Scenario Generation Scripts and Data

The following section explains:

1. **The folder hierarchy necessary for climate scripts and data to function properly**
2. **How to download the climate scripts and data**
3. **Where to place these files within your newly created folder structure**

Creating folders for R scripts and input data

AgMIP climate scripts require the below directory structure. We recommend that you use this folder hierarchy as this is the easiest approach for running the AgMIP Climate Scenario scripts. The hierarchy of the folders should look as follows (where blue = folders, purple = files, green = description, red = important information):



We now provide you with the folder structure already created. The first link of the next section, **Downloading R scripts and data from WebDrive**, is the zipped folder structure that already contains the R scripts, test files, AgMIP Excel file template, WorldClim datasets and latitude and longitude datasets for GCMs in the correct folder locations. Additionally, you will have to download the GCM climate data and place these files into "~/R/data/CMIP5/climfiles".

IMPORTANT: R is case sensitive so it is important to preserve the downloaded folder hierarchy for the AgMIP Climate scripts to function correctly.

★Downloading R scripts and data from WebDrive

The next step will be to download the climate data and R scripts from WebDrive (links provided on the next couple pages). This is NASA Goddard's Online File Depot and has been set up by Alex Ruane. To gain access to these files, use the username and password provided below.

WebDrive Log In Information	
Username	aruane
Password	AgMIPRRTs
Expiration Date	November 23, 2013

The provided links have a 30 day expiration date and the files were posted on October 24, 2013, and thus will not be available after November 23, 2013. If you are attempting to download these files after this date, contact either Alex Ruane at **alexander.c.ruane@nasa.gov** or Nicholas Hudson at **nih2106@columbia.edu**.

You will be downloading GCM files that use RCP 4.5 and RCP 8.5 as well as the latitude and longitude files needed to properly read the GCM files.

Not all of the files that you will be downloading will be described in this Guide, but they will be discussed in future versions.

Below are the links for the required input data and R scripts along with a brief description of the files and the folder destination where the files should be placed within your newly created folder structure:

Downloading AgMIP Climate Scenario Generation Scripts and Data - 12

R scripts, test climate files, and AgMIP Excel File Template download location:
https://webdrive.gsfc.nasa.gov/longauth/600/nicholas.hudson/HEr80oC

1. The above link is the zipped folder structure containing the R scripts, test files, AgMIP Excel file template, WorldClim datasets and latitude and longitude datasets for GCMs in the correct folder locations. **We advise that you download the most recent versions of these scripts to ensure optimal performance and most robust analysis.**

Script Name	Brief description of functionality
acr_findspot.R	Returns the i and j coordinates of a given location given its latitude and longitude and a models lat and lon arrays
agmip_farmclimate.R	Formerly "acr_agmip022.R" and "acr_agmip021.R", produces monthly climate files from WorldClim data for *n* farms around the seed weather station. ***UPDATED for Version 2.1***
run_agmip_farmclimate.R	Runs "agmip_farmclimate.R" to produce monthly climate files in AgMIP format.
agmip_simple_delta.R	Creates delta scenarios from CMIP5 GCMs and BCSD.
run_agmip_simple_delta.R	Runs "agmip_simple_delta.R" to produce basic future scenario files in .AgMIP format.
agmip_simple_mandv.R	Formerly "acr_agmip100.R", adjusts a climate time series for AgMIP mean and variability scenarios.
run_agmip_simple_mandv.R	Formerly "acr_agmip120.R", runs "agmip_simple_mandv.R" to produce climate time series in AgMIP format.
agmip_simple2full.R	Converts basic future scenarios (Srad, Tmax, Tmin, Rain) output from "agmip_simple_delta.R" and "agmip_simple_mandv.R" into full future scenarios with relative humidity-controlled vapor pressure based upon daily Tmax.
run_agmip_simple2full.R	Runs "agmip_simple2full.R" to produce full future scenario files in .AgMIP format.
acr_agmip2metric.R	Produces a record of climate metrics in a given season
run_metrics.R	Runs "acr_agmip2metrics.R"

The R scripts are all located in the directory "~/R/r". This zip file also comes with a test baseline file, "USAM0XXX.AgMIP" located in "~/R/data/Climate/Historical" and an example future scenario created from "**run_agmip_simple_delta.R**" and "**run_agmip_simple2full.R**" that can be found in "~/R/data/Climate/Fullscenario".

Additionally, we have provided a template to create .AgMIP historical baseline files. This template is called "AgMIP Excel File Template v2.0.xls" and is located in the folder "~/R/data/Climate//Historical". This Excel template file uses a Visual Basic macro to create properly formatted base files and has been designed to place the newly created base files into the same directory in which the Excel template file is located. Therefore if you will be using "AgMIP Excel File Template v2.0.xls" to create your baseline .AgMIP files, the Excel file will not have to be moved. Please note, to use this feature in Excel, you must run Excel as an "Administrator", which can be done by right-clicking the Excel icon and selecting "Run as Administrator".

Lastly, the zip file contains WorldClim datasets in "~/R/data/WorldClim" and latitude and longitude datasets for GCMs in "~/R/data/CMIP5/latlon".

NOTE: We recommend that you keep the zip file containing the R scripts, the Excel template file and the .AgMIP test file as a back-up in the event that these files become corrupted. This is not necessary for the other zip files you will be downloading in the remaining four links.

2. Place the remaining files ***listed below*** (all CMIP5 input files including meanpr, fwetpr1, meantasmax, meantasmin, stdtasmas, and stdtasmin) in "~/R/data/CMIP5/climfiles"

Mean precipitation and the frequency of wet days (meanpr and fwetpr1) file download location:
https://webdrive.gsfc.nasa.gov/longauth/600/nicholas.hudson/vXZZuYC

Mean maximum and minimum temperatures (meantasmax and meantasmin) file download location:
https://webdrive.gsfc.nasa.gov/longauth/600/nicholas.hudson/0erCIC3

Standard deviation of maximum and minimum temperatures (stdtasmax and stdtasmin) file download location:
https://webdrive.gsfc.nasa.gov/longauth/600/nicholas.hudson/xdIPIC3

The files contained in these zipped folders should all be placed in "~/R/data/CMIP5/climfiles" such that there are no folders located in "~/R/data/CMIP5/climfiles", just the 360 climate files.

★Creating baseline .AgMIP files with "AgMIP Excel File Template_v2.0.xls"

Before we begin running R, we will walk through an explanation of how to create baseline .AgMIP files with "AgMIP Excel File Template_v2.0.xls". We are currently seeking to create a script that will help in the historical period gap filling and bias correction according to the AgMIP protocols described in Section 4 of the **AgMIP Guide for Regional Integrated Assessment: Handbook of Methods and Procedures**, but it is useful to be able to create .AgMIP files in Excel regardless. If you prefer to create the baseline .AgMIP files manually, **Appendix 1** provides a detailed outline for creating these files in Excel.

The baseline .AgMIP file should contain the 31-year (1980-2010) daily historical climate data for a particular station or set of climate data. This section will explain how to:

1. Open the Excel file and enable macros
2. Enter your climate data into the spreadsheet and create a baseline .AgMIP file using the macro enabled functionality
3. Create baseline .AgMIP files without the macro

★Opening "AgMIP Excel File Template.xls"

The provided baseline AgMIP creation template was designed to quickly create properly formatted .AgMIP files to be used throughout the remainder of this Guide. If you have already designed your baseline files, you can skip this subsection.

> **NOTE:** This template Excel file automatically produces baseline .AgMIP files within the folder in which "AgMIP Excel File Template_v2.0.xls" is saved. Accordingly, we recommend that you leave this template file in "~/R/data/Climate/Historical" so that the created .AgMIP baseline files are placed in the correct folder location and do not have to be moved later.

The spreadsheet includes a Visual Basic macro (essentially an Excel script designed to make complicated or redundant tasks easier) which has been designed to assist with the creation of the .AgMIP file. This spreadsheet's macro is compatible with all Windows versions of Excel created since 2003. If you are using a Mac and running Excel 2008, you will not be able to run this macro as Mac's 2008 version of Excel does not use Visual Basic. All other versions of Excel should be able to run this macro. If you would like to run this macro, please open Excel as an "Administrator", which can be done by right-clicking the Excel icon and selecting "Run as Administrator". If you are unable to run the macro, or do not wish to enable this functionality,

the template can still be used to produce properly formatted baseline .AgMIP files as described in the subsection, **Creating baseline .AgMIP files without the enabled macro**.

To retain the ability of the macro, you will have to enable the macro when you open "AgMIP Excel File Template_v2.0.xls". Each version has a different way of enabling the macro. Generally, when you open the Excel file, a security alert will appear prompting you to decide whether to enable the macro or disable this feature. Enabling the macro will retain the functionality that is discussed in the next step. If you disable the macro, you can skip the next subsection and proceed to the subsection, **Creating baseline .AgMIP files without the enabled macro**, to learn how to use the template without the macro.

If you are having difficulties enabling the macro, the Windows Office website has helpful information on enabling macros for Excel versions **2003**, **2007** and versions **2010 and 2013**.

Creating baseline .AgMIP files with the enabled macro

After enabling the macro, you should see the cover sheet, named "Input Data", of the spreadsheet. Essentially all you have to do to create the baseline .AgMIP file is fill in all of the light green fields. Specifically:

1. Enter the information for your baseline file header into the "User Entered Values" section on the left in the light green fields. This includes filling out information for the header of your .AgMIP file to be created. We highly recommend that you fill in these fields to properly document the data as the AgMIP Climate scripts have been designed to automatically use this information. There are six "User Entered Values" required for the header which should be unique for each station's set of climate data.

   8 digit baseline .AgMIP file name - The first 4 digits are used to describe the location of your climate (meteorological) station. The first 2 digits are an abbreviation for the country, which can be found at the website <**http://www.web-l.com/country-codes/**> (e.g. US = United States). The second 2 digits refer to the specific site location (e.g. AM = Ames, Iowa). The fifth through eighth digits (0XXX) should remain unchanged. For example, a file created for Ames, Iowa, USA would be named "USAM0XXX.AgMIP" and "USAM0XXX" would be entered into this field. The naming convention will be described in further detail in the subsection, **Explanation of output files**.

Creating baseline .AgMIP files with "AgMIP Excel File Template_v2.0.xls" - 16

Latitude (LAT) – latitude of the station in degrees North

Longitude (LONG) – longitude of the station in degrees East

Elevation (ELEV) – elevation of the station in meters

Thermometer height (REFHT) - the height of the station thermometer in meters above the entered station elevation

Anemometer height (WNDHT) - the height of the station anemometer in meters above the entered station elevation

2. Arrange your 31-year (1980-2010) daily climate dataset in the proper column order (where Srad = solar radiation, Tmax = temperature maximum, Tmin = temperature minimum, Rain = precipitation, Wind = wind speed, Dewp = dew point, Vprs = vapor pressure, and Rhum = relative humidity) into the table in the bottom left corner of the sheet "Input Data" (in the light green fields).

   You should fill missing values with -99. If you do not have data for Wind and/or Rhum, you can retrieve this data from the Ag-MERRA dataset. Dewp and Vprs will require additional conversion and can be left as missing (entered as -99) for the purposes of the R routines described in this Guide.

   Upon entering the data correctly into these columns, the orange boxes' color should turn light green and display "Yes".

3. Once the data has been arranged correctly, simply press the green button titled "Create .AgMIP file" to produce your new baseline .AgMIP file. This new file will be created in the same file you have positioned "AgMIP Excel File Template_v2.0.xls". Confirm the presence of your new baseline .AgMIP file in "~/R/data/Climate/Historical". If you have successfully produced your baseline .AgMIP file, you can proceed to the next section, **Running AgMIP Climate Scenario Generation scripts**.

Creating baseline .AgMIP files without the enabled macro

NOTE: This subsection is only for individuals who have not been able to enable the macro or who have opted not enable the macro. If you have successfully created your .AgMIP baseline file, you can proceed to the next section, **Running AgMIP Climate Scenario Generation scripts**.

If the macro will not work or you have chosen not to enable the macro, the template can still useful for you. Follow steps 1-2 in **Creating baseline .AgMIP files with the enabled macro** to correctly enter your data into the first sheet (Input Data) of "AgMIP Excel File Template_v2.0.xls".

After you have entered your header information and climate data into the light green fields, go to the second sheet, Baseline Data. This shows the properly formatted data and header. All you have to do to create the .AgMIP file is to save this sheet. To do this, follow these steps:

1. Select "File > Save As"
2. Select the location "~/R/data/Climate/Historical/"
3. In "File name:" enter the name of your baseline file in quotes. That is, enter the name you have entered into the field **8 digit baseline .AgMIP file name** on the sheet "Input Data" with the .AgMIP extension. For example, if you entered "USAM0XXX" into that field, enter "USAM0XXX.AgMIP" into the "File name:" field including the quotes.
4. In "Save as type:" select "Formatted Text (Space Delimited)
5. Select "Save"
6. A warning will appear alerting you that this format will not support multiple sheets. Select "OK".
7. There will be another warning about compatibility issues. Select "Yes".
8. Your file should now be saved, however, you will want to close the now altered Excel spreadsheet and select "Don't Save" to ensure the initial "AgMIP Excel File Template_v2.0.xls" is not altered in this process.

The macro actually works around this "Don't Save issue" by copying and pasting the data from the second sheet (Baseline Data) onto a new workbook. This can be difficult though as older versions of Excel do not have the functionality of Paste Special as the newer versions (both numerical and columnar formatting need to be retained). We encourage users to follow the above workflow and only paste the data into a new workbook if they feel comfortable ensuring that the formatting of the data is not lost in the pasting process.

Confirm the presence of your new baseline .AgMIP file in "~/R/data/Climate/Historical". If you have successfully produced your baseline .AgMIP file, you can proceed to the next section, **Running AgMIP Climate Scenario Generation scripts**.

★Running AgMIP Climate Scenario Generation scripts

At this point, you should have:

- Downloaded and installed R and necessary packages as explained in the section **Installation**
- Downloaded the input data and R scripts placing these files into the proper folder structure as described in the section **Downloading AgMIP Climate Scenario Generation Scripts and Data**
- Created your baseline .AgMIP files as outlined in the section **Creating baseline .AgMIP files with "AgMIP Excel File Template_v2.0.xls"**

If you have accomplished the above, you are now ready to run the AgMIP Climate scripts in R.

The following section will explain:

1. The input variables that will be modified for each of the run scripts
2. How to modify the run scripts
3. How to source the run scripts
4. An explanation of the output files

The subsection **Explanation of input variables to be changes in the run scripts** details the input variables that must be defined in the run scripts, the subsection **Modifying variables in the run scripts** generalizes how to prepare the run script and the subsection **Sourcing the run scripts** demonstrates how to run the script. If you have any questions with the naming convention imposed on the output files, please refer to the subsection **Explanation of output files**.

★Explanation of input variables to be changed in the run scripts

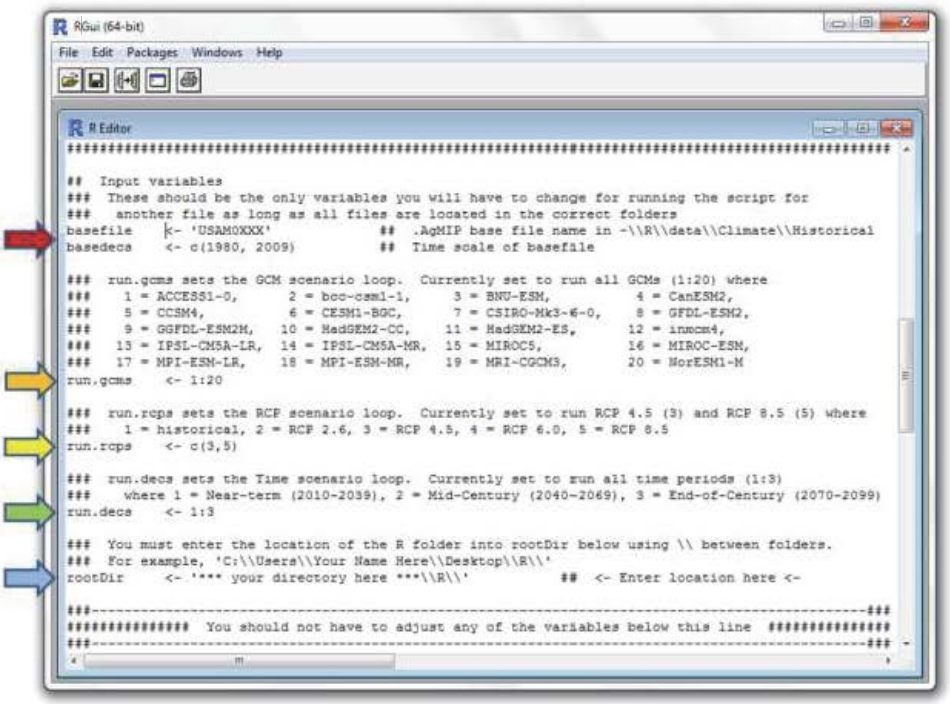
We will be changing the run scripts to reflect the information for your specific location and analytical requirements. The run scripts all begin with **"run"** and call the scripts that are identically named but do not begin with "run" (e.g. "**run_agmip_farmclimate.R**" calls "agmip_farmclimate.R" and "**run_agmip_simple_delta.R**" calls "agmip_simple_delta.R"). These scripts have been designed so that you only have to edit the run scripts and should not have to open the other scripts.

Running AgMIP Climate Scenario Generation scripts - 20

Essentially, the run scripts set the variables and parameters of the analysis. These run scripts are also designed to loop through multiple scenarios, thus producing many .AgMIP files with multiple scenario changes imposed upon the baseline data (different emission scenarios or future time periods, for example).

All of the run scripts have been similarly designed and share many of the same input variables. To simplify the explanation for using these AgMIP Climate scripts, we have provided a list of the input variables in this subsection that will need to be changed prior to running, or "sourcing", of the scripts. To clarify, each run script will require that some, but not all, of the input variables listed in this subsection be defined.

We recommend that you read through this subsection to become familiar with the input variables that you will be changing. It is our intention that this subsection will be used as a reference later if you have a question about a particular input variable. In the next subsection, Modifying variables in the run scripts, we will describe how to change these input variables. Below is a screenshot of the "Input Variables" section of the script "run_agmip_simple_delta.R".



Colored arrows identify the input variables that will need to be adjusted for this run script. The "#" symbol is used to "comment out" lines and provides you with information about the input variables. The script skips lines that have been commented when it is being sourced.

The next few pages describe the input variables that you will be required to adjust prior to sourcing the run scripts.

rootDir – This variable, as identified by the blue arrow in the screenshot on the previous page, sets the location, or root directory, of your "~/R/" folder discussed in the subsection, **Creating folders for R scripts and input data**. If you created the recommended folder structure, defining this variable is straightforward. There is a line in every run script that reads:

```
rootDir     <- '*** your directory here ***\\R\\'
```

Simply replace the text "******* your directory here*******" with the location of your newly created R directory in the script using double forward slashes (\\) to separate folders. For example, if the location of the R folder is

```
C:\Users\Your Name Here\Desktop\R\
```

then the **rootDir** should look as follows

```
rootDir     <- 'C:\\Users\\Your Name Here\\Desktop\\R\\'
```

IMPORTANT: The variable **rootDir** should not change from run to run. We recommend that you save the run script with updated **rootDir** to reflect the location of "~/R/" so you do not have to enter this information for every run. The other input variables should be changed with each new run to reflect the specific parameters of your current analysis.

basefile – This is the **8 digit baseline .AgMIP file name** described in the subsection **Creating baseline .AgMIP files with the enabled macro** and identified by the red arrow on the previous page. The first four digits describe the location of the station/site while the last four digits denote the type of scenario that was imposed on the historic data. Specifically, the first 2 digits are an abbreviation for the country, which can be found at the website <**http://www.web-l.com/country-codes/**>, while the second 2 digits refer to the specific site location and are up to you to assign. For a baseline file, the last four digits should be "0XXX". For example, we have

defined the **basefile** for Ames, Iowa, USA to be "USAM0XXX". Thus the run script input variable line would look like

```
basefile    <- 'USAM0XXX'
```

More information about the naming convention can be found in the subsection, **Explanation of output files**.

seedfile – Similar to **basefile, seedfile** is the 8 digit code of your baseline climate file. The input variable **seedfile** is used in the script "**run_agmip_farmclimate.R**" as this will be the dataset from which other local farm sites' climate files will be constructed. For example, the 8 digit code of the **seedfile** would be "KEMB0XXX" if the baseline AgMIP file was named "KEMB0XXX.AgMIP".

shortregion – Another input variable used exclusively with "**run_agmip_farmclimate.R**", **shortregion** is a 2 digit identifier used for a particular region for which you will be producing multiple files. Typically, it is sufficient to simply strip off the country code. For example, the country code "KE" can be stripped off the **seedfile** "KEMB0XXX" leaving the regional code "MB". The resulting output files from "**run_agmip_farmclimate.R**" will be named "MB010XFX.AgMIP", "MB020XFX.AgMIP", "MB030XFX.AgMIP"…

end.code – This input variable, used exclusively in "**run_agmip_simple2full.R**", denotes the last two (seventh and eighth) digits of the files to be adjusted. For example, if you want to adjust all of the files of the structure "USAM**XA.AgMIP" with a baseline file of "USAM0XXX.AgMIP" to the full format, the
would be "XA". This would set the run script to cycle through the scenarios (defined by , **run.rcps**, and **run.decs**) of all the files in "~/R/data/Climate/Simplescenario" that begin with "USAM" and end with "XA".

basedecs – This variable, also identified by the red arrow in the screenshot, assigns the beginning and end year of the dataset's 30-year time interval. Typically, the test file runs from January 1, 1980 to December 31, 2009, thus the years entered for the test file's 30-year time interval are 1980 and 2009. To assign
seedfile – Similar to **basefile, seedfile** is the 8 digit code of your baseline climate file. The input variable **seedfile** is used in the script "**run_agmip_farmclimate.R**" as this will be the dataset from which other local farm sites' climate files will be constructed. For example, the 8 digit

code of the **seedfile** would be "KEMB0XXX" if the baseline AgMIP file was named "KEMB0XXX.AgMIP".

shortregion – Another input variable used exclusively with "**run_agmip_farmclimate.R**", **shortregion** is a 2 digit identifier used for a particular region for which you will be producing multiple files. Typically, it is sufficient to simply strip off the country code. For example, the country code "KE" can be stripped off the **seedfile** "KEMB0XXX" leaving the regional code "MB". The resulting output files from "**run_agmip_farmclimate.R**" will be named "MB010XFX.AgMIP", "MB020XFX.AgMIP", "MB030XFX.AgMIP"…

end.code – This input variable, used exclusively in "**run_agmip_simple2full.R**", denotes the last two (seventh and eighth) digits of the files to be adjusted. For example, if you want to adjust all of the files of the structure "USAM**XA.AgMIP" with a baseline file of "USAM0XXX.AgMIP" to the full format, the
would be "XA". This would set the run script to cycle through the scenarios (defined by , **run.rcps**, and **run.decs**) of all the files in "~/R/data/Climate/Simplescenario" that begin with "USAM" and end with "XA".

basedecs to run from 1980 to 2009, this input variable would be assigned as

```
basedecs      <- c(1980,2009)
```

If you have data for 2010, you have the option of either selecting the time period from 1980 to 2009 or 1981 to 2010. If you chose to select 1981 to 2010, you would enter the input variable as

```
basedecs      <- c(1981,2010)
```

to assign
seedfile – Similar to **basefile**, **seedfile** is the 8 digit code of your baseline climate file. The input variable **seedfile** is used in the script "**run_agmip_farmclimate.R**" as this will be the dataset from which other local farm sites' climate files will be constructed. For example, the 8 digit code of the **seedfile** would be "KEMB0XXX" if the baseline AgMIP file was named "KEMB0XXX.AgMIP".

shortregion – Another input variable used exclusively with "**run_agmip_farmclimate.R**", **shortregion** is a 2 digit identifier used for a particular region for which you will be producing multiple files. Typically, it is sufficient to simply strip off the country code. For example, the

country code "KE" can be stripped off the **seedfile** "KEMB0XXX" leaving the regional code "MB". The resulting output files from "**run_agmip_farmclimate.R**" will be named "MB010XFX.AgMIP", "MB020XFX.AgMIP", "MB030XFX.AgMIP"…

end.code – This input variable, used exclusively in "**run_agmip_simple2full.R**", denotes the last two (seventh and eighth) digits of the files to be adjusted. For example, if you want to adjust all of the files of the structure "USAM**XA.AgMIP" with a baseline file of "USAM0XXX.AgMIP" to the full format, the
would be "XA". This would set the run script to cycle through the scenarios (defined by , **run.rcps**, and **run.decs**) of all the files in "~/R/data/Climate/Simplescenario" that begin with "USAM" and end with "XA".

basedecs to run over this time scale. Generally you should not have to change this input variable.

headerplus – This variable allows you to enter additional information into the first line of the produced AgMIP files. Typically it is sufficient to simply enter in the location of the site (Ames, Iowa, USA or Embu, Kenya, for example). Occasionally it is useful to include information about where the file data is from or how the file data was calculated. You should not have to change this input variable, but feel free to include additional information as you see appropriate.

run.gcms – This variable, identified by the orange arrow, is used to control which GCMs will be used to create the output files. Below are two tables of the GCMs with their corresponding value.

GCM	run.gcms value
ACCESS1-0	1
bcc-csm1-1	2
BNU-ESM	3
CanESM2	4
CCSM4	5
CESM1-BGC	6
CSIRO-Mk3-6-0	7
GFDL-ESM2	8
GGFDL-ESM2M	9
HadGEM2-CC	10

GCM	run.gcms value
HadGEM2-ES	11
inmcm4	12
IPSL-CM5A-LR	13
IPSL-CM5A-MR	14
MIROC5	15
MIROC-ESM	16
MPI-ESM-LR	17
MPI-ESM-MR	18
MRI-CGCM3	19
NorESM1-M	20

The run scripts are set to run through all 20 of the GCMs will the following line:

```
run.gcms      <- 1:20
```

The script is designed to run through the GCMs as they are ordered in the variable gcmname (the same ordering as appears in the table above). The ordering of the GCMs is also provided in the commented lines directly above this input variable (as can be seen in the screenshot). Say, for example, you want to run the script for BNU-ESM2M, HadGEM2-CC and MIROC5 which are positioned as the 3rd, 10th and 15th in gcmlist. You would then define as

```
run.gcms      <- c(3,10,15)
```

If you only want to run the first five GCMs follow the same procedure and enter the line

```
run.gcms      <- c(1,2,3,4,5)
```

Or alternatively,

```
run.gcms      <- 1:5
```

run.rcps – This input variable, identified by the yellow arrow, is used to control which emissions scenarios (RCPs) will be used to create the output files. Below is a table denoting the values of **run.rcps** along with the corresponding emissions scenario (RCPs).

RCP	run.rcps value
Historical	1
RCP 2.6	2
RCP 4.5	3
RCP 6.0	4
RCP 8.5	5

NOTE: While the script is designed to run RCP 2.6 (2) and RCP 6.0 (4), the data for these two emissions scenarios has not been included in the data provided by the links in the subsection **Downloading R scripts and data from WebDrive**. Thus, you should only define **run.rcps** as a 1, 3, or 5 (historical, RCP 4.5, or RCP 8.5) for the script to function correctly.

As can be seen in the screenshot, the run script "run_agmip_simple_delta.R" is set to run RCP 4.5 (3) and RCP 8.5 (5) with the following line:

```
run.rcps      <- c(3,5)
```

If you wish to produce files from another emissions scenario simply redefine **run.rcps**. For example, if you only want to run the script from the emissions scenario RCP 8.5 (5), set the input variable to 5 using the following line:

```
run.rcps      <- 5
```

If you want to run the script for the historical scenario (1) as well as RCP 4.5 (3) and RCP 8.5 (5) you can use the line

```
run.rcps      <- c(1,3,5)
```

IMPORTANT: Some of the run scripts ("**run_agmip_simple_mandv.R**" in particular) require a large amount of local memory. As such, we recommend that you run ***one emissions scenario at a time*** for "**run_agmip_simple_mandv.R**". If the script breaks while you are running one of the AgMIP Climate scripts due to memory issues, consider reducing the number of emissions scenarios or number of future the time periods. After the run has successfully completed, reboot your computer (to reset your local memory) and run the other time periods and emissions scenarios you will require.

run.decs – Another input variable, as identified by the green arrow, used to control the output files produced by the run scripts. This input variable is used to control which time periods will be used. Below is a table of the three preset future time periods.

Future time period	run.decs value	First year	Last year
Near-term	1	2010	2039
Mid-Century	2	2040	2069
End-of-Century	3	2070	2099

Similar to and **run.rcps**, this variable is easily adjusted. Below is a line demonstrating how to produce output files for Near-term and End-of-Century future time scenarios

```
run.decs      <- c(1,3)
```

If you wish to produce files over just the Mid-Century time period, use the line provided below.

```
run.decs      <- 2
```

datashort – This variable is used to define your sub-region for WorldClim files and is used exclusively by the script "**run_agmip_farmclimate.R**". Your region is determined by the table below and you should enter your region into the input variable **datashort**.

Datashort	Region Name	S. Lat	N. Lat	W. Lon	E. Lon
EAfrica	Eastern Africa	20°S	22°N	20°E	53°E
WAfrica	Western Africa	3°N	25°N	18°W	15°E
SAfrica	Southern Africa	36°S	8°S	11°E	51°E
Pakistan	Pakistan	23°N	38°N	60°E	80°E
IGB	Indo-Gangetic Basin	15°N	38°N	65°E	97°E
SIndiaSriLanka	S. India and Sri Lanka	5°N	30°N	70°E	90°E

If, for example, your region is located at 5°N, 35°E, you would enter the input variable as

```
datashort     <- 'EAfrica'
```

due to your location in the subregion of Eastern Africa.

sitelat – Another input variable used exclusively with "**run_agmip_farmclimate.R**". This input variable defines the series of site latitudes for which you are creating climate baseline files. This variable should be defined in terms of degrees North such that the values range from -90°N (South Pole) to 90°N (North Pole).

For example, below is the line from the run script that will produce 3 output .AgMIP files for farms at latitudes -0.7°N, -0.6°N and -0.75°N respectively.

```
sitelat     <- c(-00.70, -00.60, -00.75)
```

Running AgMIP Climate Scenario Generation scripts - 28

IMPORTANT: AgMIP Climate Scenario Generation scripts since version 2.0 of the Guide extract information from the header of the .AgMIP files, thus the coordinates of the **seedfile** should not be included in the **datashort** – This variable is used to define your sub-region for WorldClim files and is used exclusively by the script **"run_agmip_farmclimate.R"**. Your region is determined by the table below and you should enter your region into the input variable **datashort**.

sitelon – Same as **datashort** – This variable is used to define your sub-region for WorldClim files and is used exclusively by the script **"run_agmip_farmclimate.R"**. Your region is determined by the table below and you should enter your region into the input variable **datashort**.

Datashort	Region Name	S. Lat	N. Lat	W. Lon	E. Lon
EAfrica	Eastern Africa	20°S	22°N	20°E	53°E
WAfrica	Western Africa	3°N	25°N	18°W	15°E
SAfrica	Southern Africa	36°S	8°S	11°E	51°E
Pakistan	Pakistan	23°N	38°N	60°E	80°E
IGB	Indo-Gangetic Basin	15°N	38°N	65°E	97°E
SIndiaSriLanka	S. India and Sri Lanka	5°N	30°N	70°E	90°E

If, for example, your region is located at 5°N, 35°E, you would enter the input variable as

```
datashort     <- 'EAfrica'
```

due to your location in the subregion of Eastern Africa.

sitelat, but with longitude. This variable should be defined in terms of degrees East such that 90°W should be entered either as -90°E or as 270°E. For example, below is the line from the run script.

```
sitelon     <- c(37.54, 37.58, 37.69)
```

This example denotes that the run script will produce 3 output .AgMIP files for farms at longitudes 37.54°E, 37.58°E and 37.69°E respectively.

Modifying variables in the run scripts

NOTE: For the purposes of this tutorial, we recommend that you perform the following modifications of the AgMIP Climate scripts using the R GUI to gain some familiarity with R's user interface. However, if you are familiar with R and feel more comfortable amending the scripts in your preferred text editor, feel free to do so.

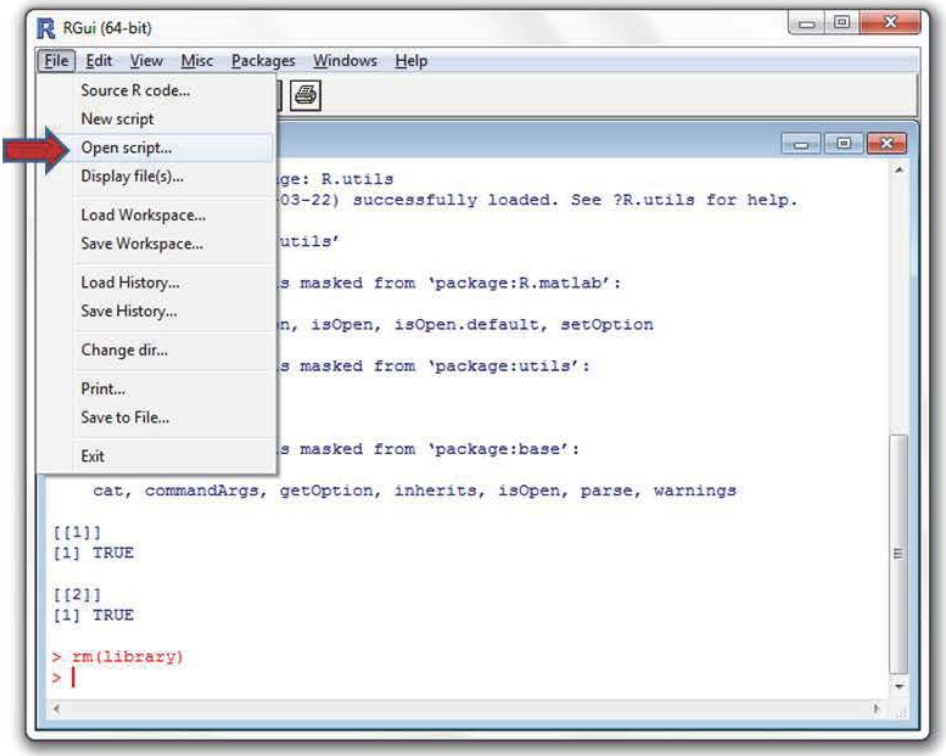
This subsection explains the steps that are required to prepare a run script for use on your computer. This subsection generalizes how to make the adjustments to the script. The subsection, **Suggested workflows for the run scripts**, explains specifically how to run each of the AgMIP Climate run scripts. Like the previous subsection, **Explanation of input variables to be changed in the run scripts**. We recommend that you read through this subsection to get an idea of how to modify the run scripts and refer to it later if you have questions when working through the workflows presented in the subsection, **Suggested workflows for the run scripts**. The following section will explain:

1. How to open a script in R
2. How to modify **rootDir** to tailor the run script for your computer
3. How to modify the other input variables

Running AgMIP Climate Scenario Generation scripts - 30

We will begin by opening the run script you are interested in running. After opening R, there are a couple ways you can open the run script. You can either

- **Select "File > Open script…" from the menu bar along the top of the R window as indicated by the red arrow, or**
- **Press the open button, , in the toolbar (hidden in the below image by the drop-down window).**



If you followed the recommended folder structure outlined in the subsection, Creating folders for R scripts and input data, the scripts will be located in the folder "~/R/r/".

Once you have opened the run script in the R editor, the next step is to adjust **rootDir** to reflect the location of your "~/R/" folder. Scroll down section "Input variables" below the run script heading to the line that reads:

```
rootDir     <- '*** your directory here ***\\R\\'
```

Enter the path to your root directory, that is the location of your "~/R/" folder, discussed in the subsection, **Creating folders for R scripts and input data** in the run script using double forward slashes (\\) to separate the folders. For an example, refer to **rootDir**.

> **NOTE:** If you will be running these scripts for multiple station locations, we recommend that you save the run script at this point in time. The input variable **rootDir** should not change from run to run and thus you can save the run script to avoid having to adjust this variable for every run. The other input variables will be changed for different runs, so saving the script here is a logical saving point.

After **rootDir** is assigned, you will not have to change any of the other folder locations as the folder structure is hardwired into the scripts. The AgMIP Climate scripts were intentionally designed this way to make this process as simple as possible.

After saving the run script, you will have to define the input variables (described in the previous subsection, **Explanation of input variables to be changed in the run scripts**) prior to every run. You can edit the script either in R editor or another text editor of your choosing. We will continue to use R editor in this Guide.

Each AgMIP Climate Scenario Generation script has a section for the input variables that must be assigned to run the script successfully. The next section, **Suggested workflows for the run scripts**, outlines the input variables that will need to be defined. These input variables will need to be defined prior to every run. After properly defining these input variables, you would be ready to run, or source, the AgMIP climate script.

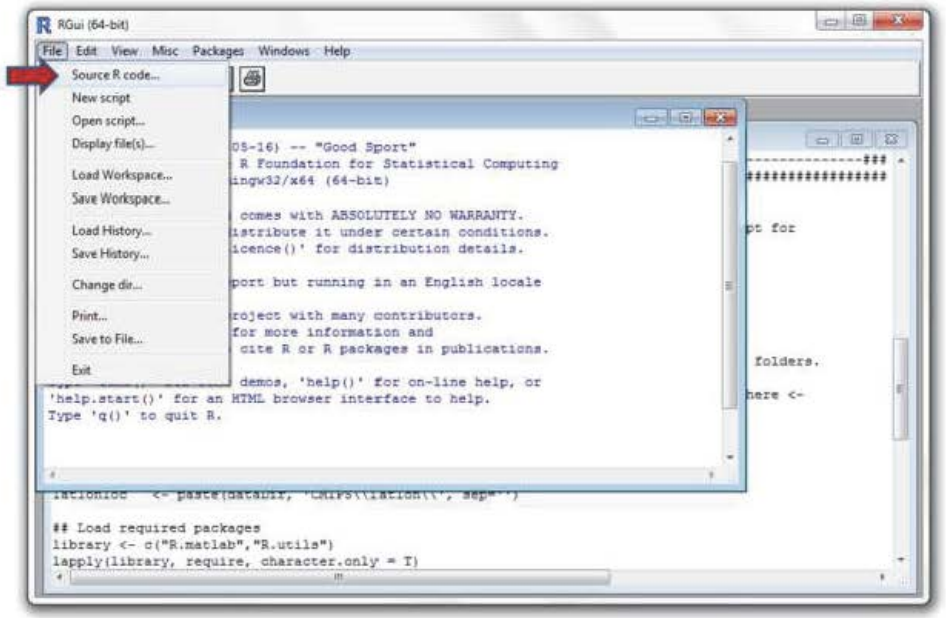
> **IMPORTANT:** At this point you have to save the run script to "~/R/r/". ***We recommend that you save the script as a separate file with a unique name*** (e.g. "run_agmip_farmclimate_stn1" or "run_agmip_simple2full_USAM_delta3") to reflect the particular station, dataset or analysis. This will retain the initial AgMIP run script as a template for future analyses.

Running AgMIP Climate Scenario Generation scripts - 32

Sourcing the run scripts

After defining the input variables of your run script and saving the run script with a unique name to "~/R/r/", return to the R Console window. To run your amended run script, select "File > Source R code…" from the menu bar as is indicated by the red arrow in the screenshot below. It is important that you are in the R Console, otherwise "Source R Code" will not be an option in the File dropdown menu.

IMPORTANT: You must save the run script with your changes to the input variable definitions for the scripts to be sourced correctly.



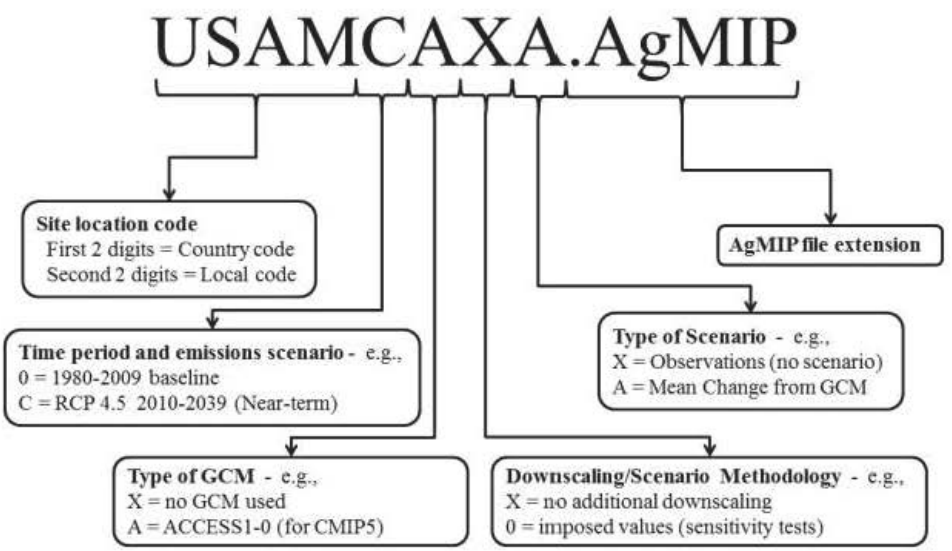
After you select "Source R code…", navigate to "~/R/r/" and select your amended and saved run script. Typically the run scripts will take a few hours to run as they are batch creating multiple files based on a variety of scenarios.

The next section, **Explanation of output files**, describes the naming convention that is used with the 8 digit AgMIP file names. The following section, **Suggested workflows for the AgMIP Climate run scripts**, outline suggested procedures for using the different AgMIP run scripts.

Explanation of output files

The provided AgMIP run scripts create a series of files that are named with an eight digit code. This naming convention was created to help convey details of the scenarios so that they may be understood by other AgMIP participants and the AgMIP IT tools.

Below is a brief explanation of the key (pages 33-34) for this code. The file in the figure below is the first file that would be created from running "**run_agmip_simple_delta.R**" with the preset parameters using the given test AgMIP baseline file, "USMA0XXX.AgMIP".



The first 4 digits, as described by **8 digit baseline .AgMIP file name** in the subsection **Creating baseline .AgMIP files with the enabled macro** and **basefile** in the subsection **Explanation of input variables to be changed in the run scripts**, are used to describe the location of the climatological (meteorological) station where your historical dataset was collected. In the above example, the code "USAM" is used to describe the location where the first 2 letters are an abbreviation for the country (US = United States). The website, <**http://www.web-**

l.com/country-codes/>, provides 2 letter codes for countries and we recommend that you use these abbreviations for the first two digits of your 8 digit code.

The second 2 digits refer to the site location and are up to you to define. For the code "USAMCAXA", the "AM" is used to denote Ames, Iowa. Use your discretion when choosing these digits. These digits should help create a unique code for your file so try to avoid redundant digits.

The fifth digit describes the time period and emissions scenario. Generally, the run scripts are designed to loop through multiple time periods and emissions scenarios when producing new files and this digit is automatically assigned to reflect the parameters imposed upon the dataset. In the example on the previous page, the fifth digit, C, denotes that the file uses RCP 4.5 over the future time period from 2010-2039. A baseline AgMIP file has a zero (0) as the fifth digit defining that the file's time period runs from 1980-2009 and does not have an imposed emissions scenario.

The sixth digit typically denotes the imposed GCM scenario from CMIP5. For the purposes of many of the analyses that will be conducted in the future, the CMIP5 GCM outputs will be used unless otherwise mentioned. In the example, the sixth digit is an "A", which tells us that this particular file had a GCM scenario imposed on the baseline data from ACCESS1-0. A baseline AgMIP file has an X as the sixth digit denoting that there was no GCM used in the creation of the file. Similar to the fifth digit, the sixth digit is typically assigned within the AgMIP run script loops.

The seventh digit is used to impose additional downscaling or sensitivity tests on the baseline dataset. Generally this variable is unchanged when using the scripts described in this Guide unless you impose downscaling or scenario methodology independently. As a result, this digit is usually X, denoting that there has been no additional downscaling.

The eighth digit tells us the type of scenario that has been imposed for this particular file. For the example code on the previous page, "USAMCAXA", the eighth digit, "A", tells us that there has been a mean change imposed a calculated from a GCM. This digit is typically assigned by the loop in the run script, but in when using the script "run_agmip_simple2full.R" you will need to identify this variable to specify files that you would like to be expanded to full files. The eighth digit is an "X" for the baseline AgMIP files, defining the file to be a dataset of daily observations.

The next two pages (pages 33-34) list the key for the fifth, sixth, seventh and eighth digits of the AgMIP file naming convention. The first four digits are user defined and thus do not require a key.

Fifth Digit is time period and emissions scenario:

0 = 1980-2009 baseline
1 = A2-2005-2035 (Near-term)
2 = B1-2005-2035 (Near-term)
3 = A2-2040-2069 (Mid-Century)
4 = B1-2040-2069 (Mid-Century)
5 = A2-2070-2099 (End-of-Century)
6 = B1-2070-2099 (End-of-Century)
S = sensitivity scenario
A = observational time period (determined in file)
B = RCP2.6 2010-2039 (Near-term)
C = RCP4.5 2010-2039 (Near-term)
D = RCP6.0 2010-2039 (Near-term)
E = RCP8.5 2010-2039 (Near-term)
F = RCP2.6 2040-2069 (Mid-Century)
G = RCP4.5 2040-2069 (Mid-Century)
H = RCP6.0 2040-2069 (Mid-Century)
I = RCP8.5 2040-2069 (Mid-Century)
J = RCP2.6 2070-2099 (End-of-Century)
K = RCP4.5 2070-2099 (End-of-Century)
L = RCP6.0 2070-2099 (End-of-Century)
M = RCP8.5 2070-2099 (End-of-Century)

Sixth Digit is source of baseline data (if baseline scenario):

X = no GCM used
0 = imposed values (sensitivity tests)
Q = Bias-corrected MERRA
T = NASA POWER
U = NARR
V = Bias-corrected CFSR
W = MERRA
Y = NCEP CFSR
Z = NCEP/DoE Reanalysis-2

Sixth Digit is GCM (if CMIP3 scenario – these are not required for AgMIP full assessments):

X = no GCM used
0 = imposed values (sensitivity tests)
A = bccr
B = cccma cgcm3
C = cnrm
D = csiro
E = gfdl 2.0
F = gfdl 2.1
G = giss er
H = inmcm 3.0
I = ipsl cm4
J = miroc3 2 medres
K = miub echo g
L = mpi echam5
M = mri cgcm2
N = ncar ccsm3
O = ncar pcm1
P = ukmo hadcm3

Sixth Digit is GCM (if CMIP5 scenario):

0 = imposed values (sensitivity tests)
A = ACCESS1-0
B = bcc-csm1-1
C = BNU-ESM
D = CanESM2
E = CCSM4
F = CESM1-BGC
G = CSIRO-Mk3-6-0
H = GFDL-ESM2G
I = GFDL-ESM2M
J = HadGEM2-CC
K = HadGEM2-ES
L = inmcm4
M = IPSL-CM5A-LR
N = IPSL-CM5A-MR
O = MIROC5
P = MIROC-ESM
Q = MPI-ESM-LR
R = MPI-ESM-MR
S = MRI-CGCM3
T = NorESM1-M

Running AgMIP Climate Scenario Generation scripts - 36

Seventh Digit is downscaling/scenario methodology:

X = no additional downscaling
0 = imposed values (sensitivity tests)
1 = WRF
2 = RegCM3
3 = ecpc
4 = hrm3
5 = crcm
6 = mm5i
7 = RegCM4
A = GiST
B = MarkSIM
C = WM2
D = 1/8 degree BCSD
E = 1/2 degree BCSD
F = 2.5minute WorldClim
W = TRMM 3B42
X = CMORPH
Y = PERSIANN
Z = GPCP 1DD

Eighth Digit is Type of Scenario:

X = Observations (no scenario)
A = Mean Change from GCM
B = Mean Change from RCM
C = Mean Change from GCM modified by RCM
D = Mean Temperature Changes Only
E = Mean Precipitation Changes Only
F = Mean and daily variability change for Tmax, Tmin, and P
G = P, Tmax and Tmin daily variability change only
H = Tmax and Tmin daily variability and mean change only
I = P daily variability and mean change only
J = Tmax and Tmin daily variability change only
K = P daily variability change only

Suggested workflows for the run scripts

The following section details the specific workflows that should be used to run the AgMIP Climate Scenario Generation scripts. The previous section, **Running AgMIP Climate Scenario Generation scripts**, has generalized how to run these scripts while this section will present detailed workflows for the AgMIP Climate Scenario Generation scripts.

If you have any questions about the input variables, refer to the subsection, **Explanation of input variables to be changed in the run scripts** or simply click on the input variable for which you have a question.

In the overall workflow, this subsection picks up after you have successfully created your baseline .AgMIP file as described in the section **Creating baseline .AgMIP files with "AgMIP Excel File Template_v2.0.xls"**. This subsection then details how to:

1. Create new baseline AgMIP files for sites in the region of your climate station using "**run_agmip_farmclimate.R**".
2. Impose mean changes on the climate variables temperature maximum (Tmax), temperature minimum (Tmin) and precipitation (Rain) based on the GCMs with different emissions scenarios and across different time scales using "**run_agmip_simple_delta.R**".
3. Impose mean and variability changes to the climate variables temperature maximum (Tmax), temperature minimum (Tmin) and precipitation (Rain) based on the GCMs with different emissions scenarios and across different time scales using "**run_agmip_simple_mandv.R**".
4. Convert file simple output files created by either "**run_agmip_simple_delta.R**" or "**run_agmip_simple_mandv.R**" to full files (including wind speed (Wind) and relative humidity (Rhum) from the baseline AgMIP file and modified dew point (Dewp), vapor pressue (Vprs) derived from changes to Tmax) using "**run_agmip_simple2full.R**".

To reiterate, the run scripts are designed to batch produce a number of .AgMIP files by calling the script of the same name but without the "run" prefix (for example, "**run_agmip_farmclimate.R**" calls "agmip_farmclimate.R" and "**run_agmip_simple2full.R**" calls "agmip_simple2full.R"). The run scripts are designed to loop through multiple scenarios to reduce the number of times you will need to run these scripts. The following workflows explain how these run scripts should be used and have some information on how they can be tailored for your needs.

run_agmip_farmclimate.R

The run script "run_agmip_farmclimate.R" creates baseline .AgMIP files for a series of locations (farms) in a given region. This script can be used to create climate files for a large number of farm locations that are close to a central weather station where the historical climate series has been quality controlled. If the farms are greater than ~100km away it may be better to pull the sites directly from Ag-MERRA dataset.

The workflow is fairly simple if you have placed all of the files in the correct location as described in **Creating folders for R scripts and input data**. All you will have to do is switch a couple of the input variables in the run script prior to each run.

To run this script,

1. Open R and then open the run script "run_agmip_farmclimate.R" to edit the input variables. You could also edit the run script in a text editor if you prefer.
2. Change the **rootDir** to reflect the location of the folder "R" and **datashort** to reflect your WorldClim sub-region.
3. Save the updated run script as your template "run_agmip_farmclimate.R" script.

Adjust the input variables **seedfile, shortregion, headerplus, datashort** – This variable is used to define your sub-region for WorldClim files and is used exclusively by the script "**run_agmip_farmclimate.R**". Your region is determined by the table below and you should enter your region into the input variable **datashort**.

Datashort	Region Name	S. Lat	N. Lat	W. Lon	E. Lon
EAfrica	Eastern Africa	20°S	22°N	20°E	53°E
WAfrica	Western Africa	3°N	25°N	18°W	15°E
SAfrica	Southern Africa	36°S	8°S	11°E	51°E
Pakistan	Pakistan	23°N	38°N	60°E	80°E
IGB	Indo-Gangetic Basin	15°N	38°N	65°E	97°E
SIndiaSriLanka	S. India and Sri Lanka	5°N	30°N	70°E	90°E

If, for example, your region is located at 5°N, 35°E, you would enter the input variable as

```
datashort     <- 'EAfrica'
```

due to your location in the subregion of Eastern Africa.

4. **sitelat**, and **sitelon** to reflect your station information (of the base file). For **headerplus**, simply enter the location of the station (for example, "Ames, Iowa, USA" or "Nioro, Senegal).
5. Save the amended script with a unique name (for example, "run_agmip_farmclimate_1.R" or "run_agmip_farmclimate_Station144.R") to "~/R/r/".
6. Confirm the presence of your baseline file, "****0XXX.AgMIP" in "~/R/data/Climate/Historical/".
7. Source (run) the script from the R Console.
8. Try not to use your computer if possible to improve run time of script.
9. After the script has completed, the baseline .AgMIP files for a series of locations should be located in "~\\R\\data\\Climate\\Historical\\". Confirm the presence of these files.

Although we did not provide you with a test file for this script, there is an example of an output from "**run_agmip_farmclimate.R**" shown in **Appendix 2**. The example file demonstrates the format of the .AgMIP files produced by this run script. This script should run quickly but will take more time depending on the number of sites for which you are producing baseline .AgMIP files.

> **Note:** When closing R, you will be asked to save your workspace. This saves the working environment (data, functions, etc.) and should not be necessary for the purposed of running the AgMIP Climate scripts.

run_agmip_simple_delta.R

This script creates delta scenarios from CMIP5 GCMs and BCSD in the AgMIP standard format. You can either use your baseline AgMIP file or the newly created AgMIP files produced by "**run_agmip_farmclimate.R**" as the input **basefile** for this run script. We are currently working on a run script that would loop through a series of **basefiles** to simplify larger batch runs.

To run this script,

1. Open R and then open the run script "**run_agmip_simple_delta.R**" to edit the input variables. You could also edit the run script in a text editor if you prefer.
2. Change the **rootDir** to reflect the location of the folder "~/R".
3. Save the updated run script as your template "**run_agmip_simple_delta.R**" script.

Adjust the input variables **basefile** and

seedfile – Similar to **basefile**, **seedfile** is the 8 digit code of your baseline climate file. The input variable **seedfile** is used in the script "**run_agmip_farmclimate.R**" as this will be the dataset from which other local farm sites' climate files will be constructed. For example, the 8 digit code of the **seedfile** would be "KEMB0XXX" if the baseline AgMIP file was named "KEMB0XXX.AgMIP".

shortregion – Another input variable used exclusively with "**run_agmip_farmclimate.R**", **shortregion** is a 2 digit identifier used for a particular region for which you will be producing multiple files. Typically, it is sufficient to simply strip off the country code. For example, the country code "KE" can be stripped off the **seedfile** "KEMB0XXX" leaving the regional code "MB". The resulting output files from "**run_agmip_farmclimate.R**" will be named "MB010XFX.AgMIP", "MB020XFX.AgMIP", "MB030XFX.AgMIP"…

end.code – This input variable, used exclusively in "**run_agmip_simple2full.R**", denotes the last two (seventh and eighth) digits of the files to be adjusted. For example, if you want to adjust all of the files of the structure "USAM**XA.AgMIP" with a baseline file of "USAM0XXX.AgMIP" to the full format, the
would be "XA". This would set the run script to cycle through the scenarios (defined by , **run.rcps**, and **run.decs**) of all the files in "~/R/data/Climate/Simplescenario" that begin with "USAM" and end with "XA".

basedecs to reflect the relevant information of your baseline AgMIP file. You can also adjust the variables , **run.rcps**, and **run.decs** if you only require a subset of these input variables.

IMPORTANT: If you are having issues completing the script due to local memory issues, consider adjusting , **run.rcps**, and **run.decs**. Running subsets will produce fewer output files and use less of your local memory. After completing such a subset it is important to reboot your computer prior to running the next subset.

4. Save the amended script with a unique name (e.g. "run_agmip_simple_delta_Stn12.R" or "run_agmip_simple_delta_Farm67.R") to "~/R/r/".
5. Confirm the presence of your **basefile** in "~\\R\\data\\Climate\\Historical\\"
6. Source (run) the script from the R Console
7. Try not to use your computer if possible to improve run time of script.

8. After the script has completed, the basic delta adjusted files should be located in ~\\R\\data\\Climate\\Simplescenario\\. Confirm the presence of these files.

The .AgMIP files produced by "**run_agmip_simple_delta.R**" only contain the climate variables Srad, Tmax. Tmin, and Rain. If you require any of the other climate variables (Wind, Dewp, Vprs, and/or Rhum) you can use "**run_agmip_simple2full.R**" to create full files. The subsection **Creating "full" files from "run_agmip_simple_delta.R" outputs** explains how to do this.

If you chose to source "**run_agmip_simple_delta.R**" with the test file, "USAM0XXX.AgMIP" to produce the simple future scenario files in .AgMIP format, you can check the first created file, "USAMCAXA.AgMIP", against the data shown in **Appendix 3**. However, the data shown in this Appendix is the output from "**run_agmip_simple_delta.R**" and "**run_agmip_simple2full.R**" so remember that the example displays data for wind speed (WIND), dew point (DEWP), vapor pressure (VPRS), and relative humidity (RHUM) as well.

run_agmip_simple_mandv.R

The script "agmip_simple_mandv.R" applies mean and variability changes to temperature maximum (Tmax), temperature minimum (Tmin) and precipitation (Rain) of the input baseline .AgMIP file. The other climate variables (Srad, Wind, Dewp, Vprs, Rhum) are not adjusted by this script.

Running this script is similar to "**run_agmip_simple_delta.R**" in that you should only have to change the root directory (**rootDir**), adjust the input variables, and the run script will impose a series of changes to the baseline file to create a batch of output files. Below is a suggested workflow for running "**run_agmip_simple_mandv.R**":

To run this script,

1. Open R and then open the run script "**run_agmip_simple_mandv.R**" to edit the input variables. You could also edit the run script in a text editor if you prefer.
2. Change the **rootDir** to reflect the location of the folder "~/R".
3. Save the updated run script as your template "**run_agmip_simple_delta.R**" script. Adjust the input variables **basefile** and **headerplus** to reflect the relevant information of your baseline AgMIP file. Change **headerplus** from "Ames, Iowa, USA" to the text with the station or site location. We recommend that you leave the text "with mean and daily

variability changes for Tmax, Tmin and P". You can also adjust the variables , **run.rcps**, and **run.decs** to run a subset of these input variables.

IMPORTANT: This run script, "**run_agmip_simple_mandv.R**" will quickly use up your local memory. We recommend that you only run one emissions scenario (as defined by **run.rcps**) and one time period (as defined by **run.decs**) per run to ensure the script finishes without encountering any memory issues. It is important to remember to restart your computer after completing a run if you intend on running another analysis.

4. Save the amended script with a unique name (e.g. "run_agmip_simple_mandv_Stn12.R" or "run_agmip_simple_mandv_Farm67.R") to "~/R/r/".
5. Confirm the presence of your **basefile** in "~\\R\\data\\Climate\\Historical\\"
6. Source (run) the script from the R Console
7. Try not to use your computer if possible to improve run time of script.
8. After the script has completed, the basic delta adjusted files should be located in ~\\R\\data\\Climate\\Simplescenario\\. Confirm the presence of these files.

The .AgMIP files produced by "**run_agmip_simple_mandv.R**" only adjust the climate variables Tmax. Tmin, and Rain. The other climate variables (Srad, Wind, Dewp, Vprs, and Rhum) are pasted into this file from the AgMIP file you specified as the **basefile**. If you require that Dewp and Vprs are updated to reflect changes in Tmax, you can use "**run_agmip_simple2full.R**" to create full files. The subsection **Creating "full" files from "run_agmip_simple_mandv.R" outputs** explains how to do this.

IMPORTANT: The script "**agmip_simple_mandv.R**" occasionally has difficulties applying the mean and variability changes without significantly changing the distribution and will notify you that there is a poor fit. The script is designed to then loop through and try to apply the changes two more times. If the run script is unable of applying the changes after three tries, the script will fill in that particular month with -99 values.

If you encounter this issue, you can try to run the script again (after it has completed creating the other output files and rebooting your computer) specifically for this file by using , **run.rcps**, and **run.decs**. If the problem persists, please contact us so we can help you resolve this issue and produce the .AgMIP files you require for your research.

run_agmip_simple2full.R

The script "agmip_simple2full.R" converts basic future scenarios (Srad, Tmax, Tmin, Rain) into full scenarios with relative humidity-controlled dew point and vapor pressure based upon daily Tmax. The script fills Wind and Rhum with the data from the input baseline AgMIP file and computes new values for Dewp and Vprs based on Tmax and Rhum.

The run script can be used for output AgMIP files from "run_agmip_simple_delta.R" and from "run_agmip_simple_mandv.R". Both have slightly different workflows, thus there are two subsections, **Creating "full" files from "run_agmip_simple_delta.R" outputs** and **Creating "full" files from "run_agmip_simple_mandv.R" outputs**, describing how to use this run script.

Creating "full" files from "run_agmip_simple_delta.R" outputs

After running "run_agmip_simple_delta.R" you will have a series of basic delta adjusted .AgMIP files located in "~/R/data/Climate/Simplescenario/". These new AgMIP files contain adjusted data for temperature maximum (Tmax), temperature minimum (Tmin) and precipitation (Rain) as well as the baseline data for solar radiation (Srad).

If you require the full delta adjusted .AgMIP files with wind speed (Wind), dew point (Dewp), vapor pressure (Vprs), and the relative humidity (Rhum), you will have to run the script "run_agmip_simple2full.R". This run script will paste the baseline values for Wind and Rhum and will calculate new values for Dewp and Vprs using relative humidity controlled vapor pressure based on daily Tmax..

> **IMPORTANT:** The script, "run_agmip_simple2full.R", uses the outputs from "run_agmip_simple_delta.R" to create the full delta adjusted .AgMIP files. Thus "run_agmip_simple_delta.R" **must be run prior to** "run_agmip_simple2full.R" for the script to function correctly.

To run this script,

1. Open R and then open the run script "run_agmip_simple2full.R" to edit the input variables. You could also edit the run script in a text editor if you prefer.

2. Change the **rootDir** to reflect the location of the folder "~/R".
3. Save the updated run script as your template "**run_agmip_simple2full.R**" script.

Adjust the input variables **basefile** and

to reflect the relevant information of your baseline AgMIP file. For AgMIP files produced by "**run_agmip_simple_delta.R**", the variable

should be defined as "XA" unless you have made other downscaling adjustments to the files. You should also adjust the variables , **run.rcps**, and **run.decs** to run a subset of these input variables based on the files you produced by "**run_agmip_simple_delta.R**" and the files for which you require a full climate dataset.

4. Save the amended script with a unique name (e.g. "run_agmip_simple2full_1.R" or "run_agmip_simple2full_deltas.R") to "~/R/r/".
5. Confirm the presence of your **basefile** in "~/R/data/Climate/Historical/" as well as the simple files to be converted in "~/R/data/Climate/Simplescenario/".
6. Source (run) the script from the R Console
7. Try not to use your computer if possible to improve run time of script.
8. After the script has completed, the basic delta adjusted files should be located in ~\\R\\data\\Climate\\Fullscenario\\. Confirm the presence of these files.

If you chose to run "**run_agmip_simple_delta.R**" and "**run_agmip_simple2full.R**" with the test file, "USAM0XXX.AgMIP" to produce the full future scenario files in .AgMIP format, you can check the first created file "USAMCAXA.AgMIP", against the data shown in **Appendix 3**.

Creating "full" files from "run_agmip_simple_mandv.R" outputs

If you require that the mean and variability change is also applied dew point (Dewp) and vapor pressure (Vprs), the run script "**run_agmip_simple2full.R**" can be used to expand these files. The script "**run_agmip_simple2full.R**" was updated for version 2.0 of the Guide to use the files produced by "**run_agmip_simple_mandv.R**" (found in "~/R/data/Climate/Simplescenario"). The run script calculates new daily values for Dewp, and Vprs based on the baseline relative humidity (Rhum) and the newly calculated temperature maximum (Tmax). The run script produces new "full" files located in "~/R/data/Climate/Fullscenario".

To run this script and convert the simple files to full,

1. Open R and then open the run script "**run_agmip_simple2full.R**" to edit the input variables. You could also edit the run script in a text editor if you prefer.
2. Change the **rootDir** to reflect the location of the folder "~/R".

3. Save the updated run script as your template "**run_agmip_simple2full.R**" script. Adjust the input variables **basefile**, and
to reflect the relevant information of your baseline AgMIP file. For AgMIP files produced by "**run_agmip_simple_mandv.R**", the variable
should be defined as "XF" where "X" denotes "no additional downscaling" and "F" denotes "Mean and daily variability change for Tmax, Tmin, and P". If you have made additional downscaling adjustments to your AgMIP files to be converted, adjust
accordingly. You can also adjust , **run.rcps**, and **run.decs** to run a subset of these input variables based on the files you produced by "**run_agmip_simple_mandv.R**" and the files for which you require a full climate dataset.
4. Also, you should change the **headerplus** information to read "<your site location, country> with mean and daily variability changes for Tmax, Tmin and P"
5. Save the amended script with a unique name (e.g. "run_agmip_simple2full_2.R" or "run_agmip_simple2full_mandv_1.R") to "~/R/r/".
6. Confirm the presence of your **basefile** in "~/R/data/Climate/Historical/" as well as the simple files to be converted in "~/R/data/Climate/Simplescenario/".
7. Source (run) the script from the R Console
8. Try not to use your computer if possible to improve run time of script.
9. After the script has completed, the basic delta adjusted files should be located in ~\\R\\data\\Climate\\Fullscenario\\. Confirm the presence of these files.

Next Steps…

This concludes Version 2.0 of the Guide for Running AgMIP-Climate Scenario Generation Tools with R in Windows. We will be expanding this Guide in the future to include other climate scenario tools. Your feedback is helpful and we appreciate any suggestions or recommendations you may have to improve this Guide.

If you have further questions, contact please feel free to contact Nicholas Hudson at nih2106@columbia.edu.

Thanks again for your collaboration and good luck with R!

Appendix 1: Creating .AgMIP files in Excel

This appendix describes how to create .AgMIP files in Excel manually without use of "AgMIP Excel File Template_v2.0.xls".

Here's the general approach:
1) Arrange data series in excel spreadsheet with proper column order, proper units, etc. Missing values should be filled with -99 (you can get RHUM and wind speed from the MERRA-based dataset I provided if you do not have these, but Tdew and VPRS will need additional conversion and can be left as missing for the purposes of the R routines described in this Guide.

2) Highlight all of the four columns that indicate date: @DATE, YYYY, MM, and DD (e.g., their first entries are "1980001 1980 1 1"), right click, and select "format cells". Select the number category and then change the number of Decimal places to 0.

3) Highlight the columns corresponding to SRAD, TMAX, TMIN, RAIN, WIND, DEWP, and VPRS, right click, and select "format cells". Select the number category and then change the number of Decimal places to 1.

4) Highlight the column corresponding to RHUM, right click, and select "format cells". Select the number category and then change the number of Decimal places to 0.

5) Right-click on the column letter at the top of the excel spreadsheet for the @DATE column (e.g., the "A" for Column A), select "Column Width" and set the column width to 7.

6) Right-click on the column letter at the top of the excel spreadsheet for the YYYY column (e.g., the "B" for Column B), select "Column width", and set the column width to 6.

7) Right-click on the column letter at the top of the excel spreadsheet for the MM and DD columns ("C" and "D"), select "Column width", and set the column width to 4.

8) Right-click on the column letter at the top of the excel spreadsheet for the remaining columns (SRAD to RHUM; "E" to "L"), select "Column width", and set the column width to 6.

9) Select "Save as" from the file menu and save as type "Formatted Text (Space Delimited)". Type in a full name with the extension (e.g., "USNY0XXX.AgMIP").

Appendix 1: Creating .AgMIP files in Excel - 48

10) You may need to click yes on a dialog box asking if you want to save only this sheet, and after you click that you can cancel any other dialog boxes or separate save as screens that may appear.

11) Open the .AgMIP file in notepad and then copy 5-line header from a different existing .AgMIP file and paste it on top of the AgMIP file you just created. Modify header as necessary (e.g., header, 4-letter code, latitude, longitude, elevation). TAV is the average of all Tmax and Tmin in the dataset, and AMP is half of the difference between the warmest average monthly temperature and the coolest average monthly temperature averaged over the entire dataset. REFHT is the height of the thermometer and WNDHT is the height of the anemometer (put -99 if unknown).

12) Save the file to record these modifications.

Appendix 2: Example file for "agmip_farmclimate.R"

Below is an example output data file created by "run_agmip_farmclimate.R" and located in "~\\R\\data\\Climate\\Historical\\". This data file is provided so that you can confirm that your script ran correctly. The first 32 days of the data have been provided below as well as the last 5 days of the data set (December 27-31, 2010).

*WEATHER DATA : Embu, Kenya, cast to site 01 using WorldClim-derived climatological differences

@ INSI	LAT	LONG	ELEV	TAV	AMP	REFHT	WNDHT				
MB01	-0.700	37.540	1097	20.4	2.0	-99.0	-99.0				
@DATE	YYYY	MM	DD	SRAD	TMAX	TMIN	RAIN	WIND	DEWP	VPRS	RHUM
1980001	1980	1	1	23.0	24.4	12.6	0.0	238.4	18.0	20.9	67
1980002	1980	1	2	23.8	27.1	12.1	0.0	202.7	19.6	23.1	63
1980003	1980	1	3	21.5	25.3	10.1	0.0	234.7	16.0	18.3	56
1980004	1980	1	4	23.9	26.2	12.3	0.0	220.0	15.9	18.2	52
1980005	1980	1	5	24.3	29.7	13.7	0.0	197.3	21.8	26.5	62
1980006	1980	1	6	23.1	25.9	12.1	0.0	163.4	17.7	20.4	60
1980007	1980	1	7	23.2	27.6	10.3	0.0	173.3	18.7	21.8	58
1980008	1980	1	8	24.4	27.6	12.9	0.0	213.5	16.9	19.4	51
1980009	1980	1	9	21.8	25.6	12.9	0.0	181.7	16.2	18.6	56
1980010	1980	1	10	23.8	26.7	12.5	0.0	104.6	14.7	16.9	47
1980011	1980	1	11	23.5	28.2	12.2	0.0	186.3	16.5	18.9	48
1980012	1980	1	12	19.9	25.9	14.1	0.0	199.3	15.3	17.5	51
1980013	1980	1	13	22.7	25.9	13.1	0.0	196.4	15.6	17.9	52
1980014	1980	1	14	22.4	26.2	11.6	0.0	212.4	16.5	18.9	54
1980015	1980	1	15	22.4	27.5	12.7	0.0	254.4	17.4	20.1	54
1980016	1980	1	16	20.2	25.9	15.1	0.0	179.7	17.1	19.7	58
1980017	1980	1	17	23.6	25.9	12.6	0.0	255.5	16.8	19.3	57
1980018	1980	1	18	21.3	27.1	13.3	0.0	183.0	16.8	19.2	52
1980019	1980	1	19	23.2	27.2	13.6	0.0	187.3	15.6	17.8	48
1980020	1980	1	20	24.1	27.8	11.6	0.0	237.0	17.1	19.7	51
1980021	1980	1	21	23.3	28.1	12.7	0.0	281.5	15.3	17.6	45
1980022	1980	1	22	23.6	27.1	13.1	0.0	247.3	16.1	18.5	50
1980023	1980	1	23	22.7	27.6	14.6	0.0	188.2	13.8	15.9	42
1980024	1980	1	24	21.0	29.5	14.5	0.0	146.4	16.6	19.1	45
1980025	1980	1	25	22.2	28.3	15.4	0.7	107.6	17.2	19.9	50
1980026	1980	1	26	22.1	25.2	18.1	0.3	118.5	16.7	19.2	59
1980027	1980	1	27	19.5	25.5	15.0	0.0	155.6	20.9	25.1	76
1980028	1980	1	28	3.5	25.9	16.1	0.0	148.9	19.7	23.3	68
1980029	1980	1	29	18.4	26.5	14.6	0.0	136.2	14.9	17.1	48
1980030	1980	1	30	3.1	25.8	18.1	0.0	102.9	15.2	17.4	51
1980031	1980	1	31	2.9	26.8	16.7	5.4	127.4	16.8	19.3	54
1980032	1980	2	1	20.0	26.0	16.1	0.0	150.4	17.5	20.2	59
...											
2010361	2010	12	27	18.7	26.0	17.3	5.8	77.5	16.2	18.5	54
2010362	2010	12	28	24.0	24.2	16.7	2.5	71.1	15.8	18.1	59
2010363	2010	12	29	20.1	26.0	15.0	0.0	75.4	14.4	16.5	48
2010364	2010	12	30	19.8	25.6	13.9	0.0	78.8	15.5	17.7	53
2010365	2010	12	31	23.7	26.2	14.3	0.0	70.7	13.2	15.3	44

Appendix 3: Example file for "agmip_simple_delta.R" and "agmip_simple2full.R"

Below is the data from "USAMCAXA.AgMIP", the first file that is created by "run_agmip_simple_delta.R" and "run_agmip_simple2full.R" located in "~\\R\\data\\Climate\\Fullscenario\\". This data file is provided so that you can confirm that your script ran correctly. The first 32 days of the data have been provided below as well as the last 5 days of the data set (December 27-31, 2010).

*WEATHER DATA : USAMCAXA - baseline dates maintained for leap year consistency

@ INSI	LAT	LONG	ELEV	TAV	AMP	REFHT	WNDHT				
USAM	42.017	-93.750	329	11.2	14.6	-99.0	-99.0				
@DATE	YYYY	MM	DD	SRAD	TMAX	TMIN	RAIN	WIND	DEWP	VPRS	RHUM
1980001	1980	1	1	1.2	1.3	-1.5	0.0	3.1	-0.3	6.0	89
1980002	1980	1	2	4.7	-0.3	-2.6	0.0	4.9	-7.6	3.5	58
1980003	1980	1	3	1.9	-0.3	-4.8	0.0	4.3	-9.0	3.1	52
1980004	1980	1	4	3.8	0.2	-2.6	0.0	4.1	-5.2	4.2	67
1980005	1980	1	5	1.0	0.2	-3.2	1.5	3.4	-2.5	5.1	82
1980006	1980	1	6	8.5	1.9	-7.0	2.1	9.1	-0.8	5.7	82
1980007	1980	1	7	6.7	-6.4	-15.9	0.0	8.2	-13.4	2.2	58
1980008	1980	1	8	6.7	-8.7	-16.5	0.0	2.9	-17.1	1.6	51
1980009	1980	1	9	2.2	-11.4	-20.4	1.5	3.7	-16.2	1.8	68
1980010	1980	1	10	8.0	6.3	-13.7	0.0	8.0	5.3	8.9	93
1980011	1980	1	11	4.0	11.3	-9.8	0.0	11.9	7.3	10.2	76
1980012	1980	1	12	8.6	0.8	-13.7	0.0	6.1	-10.4	2.8	43
1980013	1980	1	13	8.6	12.5	1.3	0.0	6.7	2.4	7.3	50
1980014	1980	1	14	2.1	6.9	-3.2	0.0	4.1	-1.0	5.7	57
1980015	1980	1	15	1.0	8.6	4.6	0.0	4.1	7.2	10.2	91
1980016	1980	1	16	1.9	7.5	2.4	24.4	5.6	7.4	10.3	99
1980017	1980	1	17	3.7	2.5	-2.6	1.2	5.6	-0.6	5.9	80
1980018	1980	1	18	1.4	1.3	-3.2	0.0	2.7	1.2	6.6	99
1980019	1980	1	19	1.3	1.3	-4.3	2.1	4.3	-0.0	6.1	91
1980020	1980	1	20	3.1	1.3	-8.2	0.0	2.1	-6.1	3.9	58
1980021	1980	1	21	10.4	1.3	-7.0	0.0	4.2	-0.0	6.1	91
1980022	1980	1	22	8.8	1.9	-5.4	0.0	8.2	-1.2	5.6	80
1980023	1980	1	23	2.9	-4.2	-10.9	0.0	4.0	-13.4	2.2	49
1980024	1980	1	24	5.0	6.9	-7.0	0.0	5.7	3.9	8.1	81
1980025	1980	1	25	6.9	5.8	-4.8	0.0	5.9	3.5	7.8	85
1980026	1980	1	26	7.5	-4.2	-14.3	0.0	6.1	-11.5	2.6	57
1980027	1980	1	27	5.9	-9.8	-13.2	0.0	4.5	-16.2	1.8	60
1980028	1980	1	28	9.0	-8.7	-12.6	0.0	4.6	-14.7	2.0	62
1980029	1980	1	29	4.8	-9.2	-16.5	0.0	3.8	-14.6	2.0	65
1980030	1980	1	30	12.7	-9.8	-12.6	1.5	4.7	-12.6	2.3	80
1980031	1980	1	31	4.7	-10.9	-19.8	0.0	3.8	-13.2	2.2	83
1980032	1980	2	1	6.7	-8.5	-22.8	0.0	3.0	-11.4	2.6	80
...											
2010361	2010	12	27	3.5	1.1	-0.3	0.0	2.0	-0.8	5.8	87
2010362	2010	12	28	4.8	1.7	-0.1	9.0	1.4	-0.7	5.8	84
2010363	2010	12	29	3.3	2.8	1.5	2.8	4.2	1.8	7.0	93
2010364	2010	12	30	2.6	4.0	1.7	0.0	5.1	2.0	7.1	87
2010365	2010	12	31	3.4	1.3	-1.5	0.9	5.3	-2.5	5.1	76

This page intentionally left blank

Appendix 3

This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

FOURTH ANNUAL GLOBAL WORKSHOP

OCTOBER 28 - 30, 2013
COLUMBIA UNIVERSITY
NEW YORK, NY

UKaid from the British people

USDA

AgMIP gratefully acknowledges the UK Department for International Development's UKaid for major project funding, and the US Department of Agriculture for its founding and sustained support. AgMIP additionally thanks the CGIAR Research Program on Climate Change, Agriculture and Food Security and the United States Agency for International Development for ongoing project support.

AgMIP additionally acknowledges support from The International Life Sciences Institute/The Center for Integrated Modeling of Sustainable Agriculture & Nutrition Security, Monsanto, University of Florida, The National Oceanic and Atmospheric Administration, iPlant, and Columbia University/Earth Institute.

AgMIP extends a special thank-you to Columbia University and The Earth Institute for hosting AgMIP Coordination at its Center for Climate System Research, and for additional contributions in support of the Workshop, Reception and Poster Program.

AgMIP appreciates significant in-kind contributions from:

Agricultural Research Council, South Africa
Alliance for a Green Revolution in Africa, Burkina Faso
Chinese Academy of Agricultural Sciences
Columbia University, USA
Commonwealth Scientific and Industrial Research Organisation, Australia
Consultative Group on International Agricultural Research
Dartmouth College, USA
Department of Agriculture, Fisheries and Forestry, Australia
Democritus University of Thrace, Greece
Empresa Brasileira de Pesquisa Agropecuária, Brazil
Food and Agriculture Organization of the United Nations
Foundation for Environment, Climate, and Technology, Sri Lanka
Imperial College London, UK
Institut National de la Recherche Agronomique, France
Institute of Crop Science and Resource Conservation, Germany
International Center for Tropical Agriculture, Kenya
International Crops Research Institute for the Semi-Arid Tropics
International Fertilizer Development Center, USA
International Food Policy Research Institute, USA
International Livestock Research Institute, Kenya
International Maize and Wheat Improvement Center
International Potato Center, Peru
International Research Institute for Climate and Society, USA
International Rice Research Institute, the Philippines
International Water Management Institute
Macaulay Land Use Research Institute, UK
Massachusetts Institute of Technology, USA
MTT Agrifood Research, Finland
NASA-Goddard Institute for Space Studies, USA
National Center for Atmospheric Research, USA
National Engineering and Technology Center for Information Agriculture and Nanjing Agriculture University, China
National Institute for Agro-Environmental Sciences, Japan
National Institute for Environmental Studies, Japan
Oregon State University, USA
Organisation for Economic Co-operation and Development
Pacific Northwest National Laboratory, USA
Potsdam Institute for Climate Impact Research, Germany
Project Directorate for Farming Systems Research, India
South African Sugarcane Research Institute, South Africa
Tamil Nadu Agricultural University, India
United States Department of Agriculture
Universidad Politécnica de Madrid, Spain
University of Agriculture Faisalabad, Pakistan
University of Chicago, USA
University of Florida, USA
University of Ghana
University of Illinois at Urbana-Champaign, USA
Universidade de Passo Fundo, Brazil
University of Wisconsin-Madison, USA
University of Nebraska, USA
Wageningen University and Alterra Centre for Geo-Information, the Netherlands
Washington State University, USA
World Meteorological Organization, Switzerland

AgMIP especially appreciates the contributions of the 250 workshop participants, and the considerable contributions of the EI event staff, the student volunteers, and Columbia faculty house event coordinators.

Table of Contents

Overview 2

Goals and Objectives 4

Agenda 5

Report Backs from Break-out Groups 13

Poster listings 28

Participants 31

Acknowledgements 36

Links to online materials 36

Appendix:

A. Poster titles and abstracts 37

AgMIP 4TH ANNUAL GLOBAL WORKSHOP

As the fine autumn weather continued in late October in New York City, the Agricultural Model Intercomparison and Improvement Project (AgMIP) convened its annual Global Workshop – the fourth such event since the US Department of Agriculture founded AgMIP in 2010. Members of the AgMIP community convened at Columbia University's Faculty House where Jeffery Sachs, Director of the Earth Institute, AgMIP Steering Group Co-Chairs Mannava Sivakumar and Martin Parry, and AgMIP Principal Investigators Cynthia Rosenzweig, James Jones, Jerry Hatfield, and John Antle kicked off the 3-day workshop.

The workshop brought together over 240 participants from 130 institutions representing the diversity of the AgMIP community. In addition to AgMIP core disciplines of climate, crop, and economic modeling and information technology, initiatives exploring water, soil and crop rotation, aggregation and scaling, pests and diseases, livestock and grasslands, uncertainty, ozone, and climate variability and extremes were also represented. The workshop focused on critical improvements for next-generation models, data, and decision support systems for agricultural assessments of climate change impact and adaptation, and for sustainable intensification of agriculture. Participants also advanced strategies for coordinated regional and global assessments of food security.

"You have convened at a crucial time." Jeffery Sachs said to the workshop participants, "Governments are going to need agricultural strategies and technological roadmaps. What new crop types, varieties, farm systems need to be put in place to resist climate change, create resilience, increase water efficiency, reduce heat stress, and so forth? I don't think these roadmaps exist right now."

A Speed Science session followed the introductions, in which 22 scientists shared key findings, recent accomplishments, and plans for the future. The presentations were divided into seven broad categories: Crop Model Intercomparisons and Improvement, Global Assessments, Regional Integrated Assessments, Cross-Cutting Themes, Key Interactions, New Approaches for Climate-Crop Assessment, and Data and Information Technology.

The first day was capped by an evening poster session and reception held at Columbia University's Low Library with support by The Earth Institute. G. Michael Purdy, Executive Vice-President for Research at Columbia, encouraged participants to mix and view the 65 posters displaying diverse topics such as Integrated Regional Assessments in Sub-Saharan Africa, South Asia, East Asia and Latin America, Economics, Climate, Pests and Diseases, Extreme Events, Water, Evapotranspiration,

2

Ozone, Soil and Crop Rotation, Adaptation, Data and IT, and crop specific topics such as wheat, rice, maize, soybean and potato.

"This is a great opportunity for exchange and learning in true interdisciplinary science to inform a very important problem –food security for a diverse and growing global population," said G. Michael Purdy. "Columbia University is proud to host the coordinating office of AgMIP, and is very grateful to UKaid for its major support of this endeavor, to which USDA, CCAFs, USAID, and numerous collaborating partners contribute to enable the AgMIP community to deliver robust and policy-relevant research outputs." PDFs of the posters and abstracts are available here for download.

In addition to breakouts focusing on model integration and scales, the second day of the workshop included a speed session highlighting complimentary global and regional programs CCAFS, MACSUR, USDA CAPs, Yield Gap Atlas, CIMSANS, FAO, and MODEXTREME.

At the completion of the third day breakout groups re-convened in plenary to present report backs from their sessions. PDFs of the reports as well as presentations from the workshop are available at http://www.agmip.org/feature-view/hats-off-to-the-4th-annual-agmip-global-workshop/.

Many of the groups made plans to meet again and collaborate on research and publications. Some groups like Pests and Diseases will be new to AgMIP while others will continue to build on work initiated previously. All will try to incorporate their findings into integrated assessments of food security on both the regional and global scale. It is these assessments, which combine information from crop, climate and economic models that will feed the next generation of decision support tools for policymakers in the coming decades.

Martin Parry, Co-Chair of the AgMIP Steering Committee remarked of the workshop, "What's obvious about this project is it's tapped into a huge latent demand… and that's why it has picked up speed so quickly." He continued, "90 -95% of the effort this week has been on improving the science. But you have also heard a call for messages, from donors and policymakers, and it can be complimentary. As one drives forward in model intercomparision and improvement, instead of a parallel path, have questions embedded in single pathway. How would the outcome from your model be altered with mitigation and adaptation?"

This is one of the questions AgMIP scientists will continue to pursue as the energy from this intensive workshop propels the teams forward into the coming year.

Attendees at AgMIP Global Workshop New York City. 3

Workshop Goals

1. Review AgMIP progress to date and set activities for coming year
2. Enable AgMIP groups to meet, report, interact, and plan
3. Develop plans to address critical improvements for next-generation models, data, and decision support systems needed for assessing climate change impacts and adaptation and for sustainable intensification
4. Advance strategy for coordinated regional and global assessments of food security

Synopsis

The 4th Annual AgMIP Global Workshop has been organized and structured to establish a shared understanding of progress to date, to enable advancement of initiatives underway, and to take on the challenge of creating a next generation of agricultural system models and decision support tools. The AgMIP Community must begin to address important and outstanding areas that are known to influence bio-physical and economic systems, and improve ways that critical investments in agriculture can be assessed in the context of a changing climate.

The Workshop begins with an overview of the current state of AgMIP. This includes a speed science session to highlight key areas of advancement – or challenges – or both – over the past year. This is intended to motivate interaction among Participants and existing AgMIP Work Groups throughout the rest of the Workshop, enabling Participants to associate with various AgMIP initiatives, and encouraging new collaborations over coffee breaks and in breakouts.

The afternoon features a work session to identify and prioritize key areas for model improvements. Motivating examples include climate extremes, crop/livestock interactions, pests/diseases/weeds, and ozone – but there are likely others also. The breakout structure for this work session is by Work Group (e.g., Global Economics, AgGRID, C3MP, etc.). AgMIP recognizes that each Work Group is planning for the coming year, and it is timely and appropriate for members to consider also next generation ideas and opportunities.

The day concludes with a reception hosted by the Columbia University Earth Institute in the Low Rotunda – a favorite academic building of cinematographers. The reception will feature posters from the AgMIP Sub-Saharan Africa and South Asia Research and Coordination teams, the AgMIP Work Groups, and the AgMIP Partners. A number of students, researchers and faculty interested in adaptation, land use, nutrition, policy, soils, and water – who might not otherwise be able to attend the workshop – will also join. The poster session allows for further detailing of results shown in brief during the day, and provides grounding for the creative thinking to come.

On Day 2 participants begin the process of developing plans to address critical improvements for next-generation models, data, and decision support systems, beginning with some perspectives from our collaborating Partners. Participants then breakout into a small number of aggregated Work Groups to consider how to collectively improve assessment of adaptation and sustainable intensification. After lunch, the Work Groups reconvene to address issues of scale. Following report-back of all groups, the participating Steering Committee Members are requested to join the AgMIP leaders in the Ivy Lounge for a discussion of the day, and to revisit priorities for Day 3.

The Day 3 morning plenary provides a glimpse of underway program planning at AgMIP, followed by a keynote address (speaker tbd) on future agricultural development. The session also poses some of the challenges of conducting integrated assessments across scales. Following Plenary, Participants breakout by the major regions in which integrated assessments are needed, as each region may have specific challenges and/or opportunities for planning and report-back. Participating Donors are invited to join the AgMIP PIs and Steering Committee Co-Chairs to share their perspectives during lunch. Lunchtime also finds the AgMIP workgroups self-organizing to organize their recommendations and highlights of work group plans for the final plenary session. The final plenary includes a presentation from the AgMIP leaders on what has been learned, and concludes with views from the AgMIP Steering Committee Co-Chairs. Following the conclusion of the Workshop, the available Steering Committee Members are requested to join the AgMIP Leaders in the Ivy Lounge to affirm plans for moving forward.

AGENDA

Day 1 – Monday, October 28th

7:30 am: Check-In, Registration, Coffee/Tea

Morning Plenary – Results from the AgMIP Research Community

8:30 am: Welcoming Remarks – Cynthia Rosenzweig, Moderator

8:35 am: Welcome from the Earth Institute – Jeffrey Sachs, Director, Columbia Earth Institute

8:50 am: Welcome, Introductions, Workshop Goals, and Goals for Day 1 – Jim Jones, Cynthia Rosenzweig, Jerry Hatfield, and John Antle

9:10 am: Climate change and global food security: a perspective on the AgMIP contribution to 20 years of study – Martin Parry

9:30 am: Global Framework for Climate Services: a Perspective on the AgMIP Contribution – Mannava Sivakumar

9:50 am: State of AgMIP – Cynthia Rosenzweig

10:15 am: Morning Break

10:45 am: AgMIP Work Group Introductions and Results: Speed Science Session – Peter Craufurd, Moderator

10:50 am: Crop Model Intercomparisons and Improvement

Wheat Team – Senthold Asseng and Frank Ewert

Maize Team – Simona Bassu, Jean-Louis Durand, and Jon Lizaso

Rice Team – Tao Li and Toshi Hasegawa

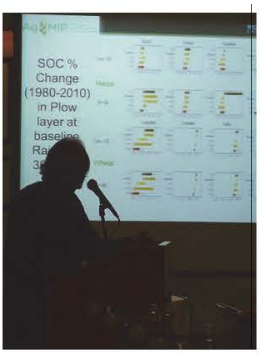
Sugarcane Team – Peter Thorburn, Abraham Singels, and Fabio Marin

Potato Team – Roberto Quiroz, Bruno Condori, and David Fleisher

Crop Model Improvement – Ken Boote and Matthijs Tollenaar

11:20 am: Global Assessments

Global Gridded Crop Model Intercomparisons – Joshua Elliott and Christoph Müller



Global Economic Model Intercomparisons – Jerry Nelson and Martin Von Lampe

11:35 am: Regional Integrated Assessments

Integrated Assessment Approach and Methods – John Antle

Sub-Saharan Africa Research – Job Kihara

South Asia – Dileepkumar Guntuku

11:55 am: Cross-Cutting Themes

Quantifying and Managing Uncertainty – Linda Mearns, Mike Rivington, and Daniel Wallach

Aggregation and Scaling Pilot – Frank Ewert and Lenny van Bussel

Representative Agricultural Pathways (RAPs) – John Antle and Roberto Valdivia

12:10 pm: Key Interactions

Soils and Crop Rotation Team – Bruno Basso

Water Resources – Jonathan Winter

12:20 pm: New Approaches for Climate-Crop Assessment

Near-Term Climate Change – Arthur Greene and Alex Ruane

Coordinated Climate-Crop Modeling Project – Alex Ruane and Sonali McDermid

AgGRID – Joshua Elliott, Cynthia Rosenzweig, and Jim Jones

12:35 pm: Data and Information Technology

Sentinel Sites – Ken Boote

Harmonizing AgMIP Site-based Data – Cheryl Porter and Chris Villalobos

Agricultural Data Journal – Sander Janssen

12:50 pm: Lunch

Afternoon Plenary: Opportunities for Model Improvement

2:00 pm: Key Processes to be integrated in Next-Generation Agricultural Models

Climate Variability and Extremes – Jerry Hatfield

Livestock and Pastures – Mario Herrero and Luis Tedeschi

Pests, Diseases, and Weeds – Karen Garrett

Ozone – Denise Mauzerall

3:00 pm: Discussion

3:20 pm: Charge to AgMIP Work Groups Breakout Session: Toward Next-Generation Model Improvements

- Summarize Work Group activities and discuss results
- Identify and prioritize key topics for model improvement and integration for impact and adaptation assessments – e.g., changes in climate extremes, crop/livestock systems, pest and disease pressures, ozone concentration; what others are important?
- Scope coming year of Work Group activities, including interactions with other groups

3:30 pm: Afternoon break

Afternoon Breakouts: Toward Next-Generation Model Improvements

4:00 pm: AgMIP Work Group Breakouts

A. Global Economics – Jerry Nelson and Dominique Van der Mensbrugghe

B. AgGRID – Joshua Elliott and Christoph Müller

C. Coordinated Climate-Crop Modeling Project (C3MP) – Alex Ruane and Sonali McDermid

D. Regional Integrated Assessments – John Antle and Roberto Valdivia

E. Crop Model Intercomparison and Improvement – Ken Boote and Peter Thorburn

F. Data, Decision Support Systems and IT – Cheryl Porter and Sander Janssen

G. Livestock and Grasslands – Mario Herrero and Jean-Francois Soussana

H. Pests/Diseases/Weeds/Ozone – Jim Jones and Karen Garrett

I. Water Resources – Jonathan Winter

J. Soils and Crop Rotation – Bruno Basso and Angela Kong

5:30 pm: Plenary Session – Report back from the breakout groups and discussion

6:30 pm: Adjourn Plenary Session

Earth Institute Reception, Low Rotunda, Columbia University

7:00 pm: Reception with AgMIP Poster Session (see also Appendix I)

- Sub-Saharan Africa and South Asia Regional Research & Coordination Team Posters
- Work Group Posters
- Partner Posters
- Others

Day 2 – Tuesday, October 29th

8:30 am: Day 2 Goals:

- Identify integration approaches for next-generation models, data, and decision support systems needed for assessing climate change impacts and adaptation and for sustainable intensification
- Lay the groundwork for coordinated regional and global assessments needed to improve

8:40 am: Opportunities for collaboration:

Speed Session on complimentary global and regional programs

CCAFS – Phillip Thornton

MACSUR – Martin Banse

USDA CAPs – Molly Jahn

Yield Gap Atlas – Lieven Claessens

CIMSANS – Dave Gustafson

FAO – Dominique van der Mensbrugghe

MODEXTREME – Ioannis Athanasiadis

Morning Breakouts – Opportunities for Model Integration

9:20 am: Charge to Integration Breakouts

- Identify approaches to address interactions across Work Groups for more comprehensive integrated biophysical and socioeconomic assessment
- Describe methods that will enable the next generation of agricultural model systems to improve assessment of adaptation and sustainable intensification

9:30 am: Model Integration Breakouts

A. Crops, Pests and Diseases, and Economics – Jim Jones, Karen Garrett, and Jerry Nelson

B. Carbon/Temperature/Water Responses, C3MP, and AgGRID – Jerry Hatfield, Ken Boote, Alex Ruane, and Joshua Elliott

C. Livestock and Pastures and Regional Integrated Assessments – Mario Herrero, Jean-Francois Soussana, and Roberto Valdivia

D. Aggregation / Scaling and Uncertainty – Frank Ewert, Linda Mearns, Daniel Wallach, and John Antle

10:30 am: Morning break

11:00 am: Model Integration Breakouts (continued)

12:45 pm: Lunch - Self-organized Work Groups

Afternoon Plenary

2:00 pm: Report back and discussion from morning breakouts

Toward Integration Across Scales

2:20 pm: Integrated Assessment across Scales – John Antle

2:45 pm: AgMIP Uncertainty Cascade – Linda Mearns

3:10 pm: Discussion

3:20 pm: Charge to Work Group: Planning and Addressing Scales

- Identify the major scaling issues in your Work Group and how they are being addressed
- Identify specific ways that your Work Group can contribute to consistent integrated assessment across scales
- Continue planning Work Group activities for the coming year

3:30 pm: Afternoon break

Afternoon Breakouts – Addressing Scales and Integration

3:45 pm: AgMIP Work Groups

A. Global Economics/RAPs – Jerry Nelson, John Antle, and Hermann Lotze-Campen

B. AgGRID – Joshua Elliott and Christoph Müller

C. Coordinated Climate-Crop Modeling Project (C3MP) – Alex Ruane and Sonali McDermid

D. Regional Integrated Assessments – Cynthia Rosenzweig, Patricia Masikati, and Geethalakshmi Vellingiri

E. Crop Model Intercomparison and Improvement – Peter Thorburn and Senthold Asseng

F. Data, Decision Support Systems and IT – Cheryl Porter, Sander Janssen, and Ioannis Athanasiadis

G. Livestock and Grasslands – Mario Herrero and Jean-Francois Soussana

H. Pests/Diseases/Weeds/Ozone – Jim Jones, Karen Garrett, Denise Mauzerall

I. Water Resources – Jonathan Winter

J. Soils and Crop Rotations – Bruno Basso and Angela Kong

5:30 pm: End-of-day plenary report back and discussion

6:15 pm: Adjourn

Steering Group check-in at Ivy Lounge

Day 3 – Wednesday, October 30th

Morning Plenary – Coordinating Regional to Global Integrated Assessments of Food Security

8:30 am: Day 3 Goal: Advance strategy for coordinated regional and global assessments with next-generation models, data, and decision support systems to address climate change and sustainability issues

8:40 am: The AgMIP Global Program – Cynthia Rosenzweig, Jim Jones, Jerry Hatfield, John Antle, Carolyn Mutter, Alex Ruane, and the AgMIP community

9:00 am: Evidence-based policymaking – Yvan Biot

9:30 am: Understanding future agricultural development: Adaptation and sustainable intensification – Stan Wood

Morning Breakouts – Linking Integrated Assessments Across Scales

10:00 am: Charge to Day 3 Breakouts on Integrated Assessment Across Scales

- How do global integrated assessment results compare with regional integrated assessment results?
- How can we design consistent and interactive regional and global assessments?
- Advance strategies for future assessments of food security and sustainable intensification

10:10 am: Mid-morning break

10:25 am: Breakouts by Region on Integrated Assessments

A. Africa – Patricia Masikati and Samuel Adiku

B. South Asia – Nataraja Subash and Ashfaq Chattha

C. Latin America and Caribbean – Eduardo Assad and Maria Travasso

D. East Asia and Australia – Fulu Tao and Peter Thorburn

E. Europe – Frank Ewert and Reimund Rötte

F. North America – Jerry Hatfield and Marca Weinberg

12:45 pm: Lunch

- Self Organized Work Groups
- Donor Forum Lunch

Afternoon Breakouts – Work Group Wrap-ups

2:00 pm: AgMIP Work Groups wrap-up sessions

A. Global Economics/RAPs – Jerry Nelson, John Antle, and Hermann Lotze-Campen

B. AgGRID – Joshua Elliott and Christoph Müller

C. Coordinated Climate-Crop Modeling Project (C3MP) – Alex Ruane and Sonali McDermid

D. Regional Integrated Assessments – Cynthia Rosenzweig, Patricia Masikati, and Geethalakshmi Vellingiri

E. Crop Model Intercomparison and Improvement – Peter Thorburn and Senthold Asseng

F. Data, Decision Support Systems and IT – Cheryl Porter, Sander Janssen, and Ioannis Athanasiadis

G. Livestock and Grasslands – Mario Herrero and J ean-Francois Soussana

H. Pests/Diseases/Weeds/Ozone – Jim Jones, Karen Garrett, Denise Mauzerall

I. Water Resources – Jonathan Winter

J. Soils and Crop Rotations – Bruno Basso and Angela Kong

3:00 pm: Report back from Regions and AgMIP Work Groups – Plans for coming year

3:30 pm: Afternoon break

Afternoon Plenary – The Way Forward

4:00 pm: What we've learned – AgMIP Next-Generation Models and Coordinated Integrated Assessments – Cynthia Rosenzweig, Jim Jones, John Antle, Jerry Hatfield, Alex Ruane, and Carolyn Mutter

4:30 pm: Feedback from Steering Group and Donor Forum – Martin Parry and Mannava Sivakumar

5:00 pm: Adjourn - Steering Group and Donor Forum check-in at Ivy Lounge

Report Backs from Break-out Groups

AgGRID Work Group Report

• Scientific Issues

Scaling, globally consistent understanding of climate impacts, harmonization and model intercomparison, informing land-use dynamics and food security.

• Group Activities and Protocols Underway

Phase one of the AgGRID GGCMI is underway since the end of May and involves an evaluation of the models against historical yield observations for the period 1948-2012 using both individual model default settings, and harmonized inputs in order to facilitate the comparison of process response. Primary aim is understanding how the models behave relative to each other, rather than making the best possible estimate of historical yields. Simulations have been submitted for 5 models, and the rest are due by 31st December 2013. Indeed we have added 2 new models during the 4th GW—the CLM-Ag model from MIT and the ISAM model from UIUC—and now count 20 model groups among our participants. Protocol design for phase II has also just begun and will be developed over the next 6 months. In essence the study will explore the response surface between CO2 concentration, temperature, water, and nitrogen availability (CTWN), with a set of protocols designed for consistency and comparability w/ CTW studies in C3MP.

• Near-term Model Improvements

Priority one is the adaptation of models to allow harmonization of management-specific processes in order to facilitate the comparison of fundamental processes (such as temperature, CO2 response). First priorities are sowing and harvest windows and fertilization. Soil harmonization is seen as important, but much too involved to tackle at this time. Priorities for improvement of model processes will be informed by the results of the harmonized simulations, but currently key areas are:

1. Nitrogen cycle in models that don't include it. (Stefan)
2. Heat stress at key stages (e.g. flowering). (Delphine)
3. Calibration and evaluation (Joshua, Nathalie, Benjamin)
4. Water balance (Benjamin, Johanna, …)
5. Crop rotations and intercropping (Christoph and Andy Challinor. Good data being compiled in South Asia. Component of the India project?)

• Next-Generation Components

Ozone, pests/pathogens/weeds, and nutrition have all been identified as important areas to be addressed in the future. Currently none of the AgGRID models are set up to deal with these processes. However, a much more pressing need is to address problems in the fundamental processes. In addition, those gridded models which are an upscaling of site models are not set up for adding new processes, instead relying on the site-based teams to develop these. That said, there are a number of large-scale gridded data products (especially for ozone) that could be exploited for use in gridded models if models can be updated to include this effect. However we will most likely have to take our cues from the field-scale modelers here.

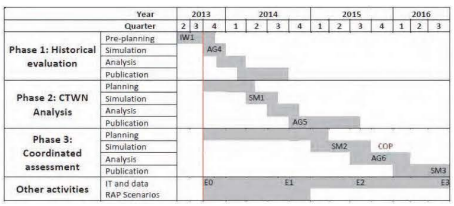
• Priorities for Integration across Disciplines

Land-use change and food security is key to address with global and regional economic teams (good AgMIP ATLAS project discussions and great interactions with regional teams and etc.).

• Contributions to Regional/Global Scale Interactions

Activities of the GGCMI are principally global scale, with regional/site scale evaluation where this is feasible/appropriate. India has been identified as a target area for a regional analysis due to the availability of high quality yield data for this region for wheat and sorghum.

• Timeline for Coming Year



• Funding Requirements

Substantial. Two proposals outstanding for GGCMI (DOE and FACCE/Belmont). Workshop proposal for Lorentz center.

• Brief lay-person-oriented description of work group activities

Global perspective with local information important for policy, economy, adaptation, and climate-smart development.

• Publications in press

Elliott, J., D. Deryng, C. Muller, K. Frieler, M. Konzmann, D. Gerten, M. Glotter*, M. Florke, Y. Wada, N. Best*, S. Eisner, C. Folberth, B. Fekete, I. Foster, S. Gosling, I. Haddeland, N. Khabarov, F. Ludwig, Y. Masaki, S. Olin, C. Rosenzweig, A. Ruane, Y. Satoh, E. Schmid, T. Stacke, Q. Tang, and D. Wisser (2013). Constraints and potentials of future irrigation water availability on global agricultural production under climate change. Proceedings of the National Academy of Sciences, in press.

Nelson, G., H. Ahammad, D. Deryng, J. Elliott, S. Fujimori, P. Havlik, E. Heyhoe, P. Kyle, M. von Lampe, H. Lotze-Campen, D. Mason-D'Croz, H. van Meijl, D. van der Mensbrugghe, C. Müller, R. Robertson, R. Sands, E. Schmid, C. Schmitz, A. Tabeau, H. Valin, and D. Willenbockel. (2013). Assessing uncertainty along the climate-crop-economy modeling chain., Proceedings of the National Academy of Sciences, in press.

Rosenzweig, C., J. Elliott, D. Deryng, A.C. Ruane, A. Arneth, K.J. Boote, C. Folberth, M. Glotter*, N. Khabarov, C. Müller, K. Neumann, F. Piontek, T. Pugh, E. Schmid, E. Stehfest, and J.W. Jones, (2013). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proceedings of the National Academy of Sciences, in press.

Piontek, F., C. Müller, T. Pugh, D. Clark, D. Deryng, J. Elliott, F. Col_on-Gonz_alez, M. Florke, C. Folberth, W. Franssen, K. Frieler, A. Friend, S. Gosling, D. Hemming, N. Khabarov, H. Kim, M. Lomas, Y. Masaki, M. Mengel, A. Morse, K. Neumann, K. Nishina, S. Ostberg, R. Pavlick, A. Ruane, J. Schewe, E. Schmid, T. Stacke, Q. Tang, Z. Tessler, A. Tompkins, L. Warszawski, D. Wisser, and H. Schellnhuber, (2013). Leaving the world as we know it: Hotspots of global climate change impacts. Proceedings of the National Academy of Sciences, in press.

• Publications in review

Deryng, D., J. Elliott, A. Ruane, C. Folberth, C. Müller, T. Pugh, E. Schmid, K. Boote, D. Gerten, J. Jones, S. Olin, S. Schaphoff, H. Yang, and C. Rosenzweig, (2013). Global opportunities for producing more crops per drop under rising atmospheric CO2. Proceedings of the National Academy of Sciences, in review.

• Publications planned

We currently plan at least 6 submissions during the publication component of GGCMI Phase I (roughly Spring 2014).

1. Historical analysis of model and ensemble hindcasting skill;
2. Agro-climatic analysis of the relative import of different methods for developing climate forcing datasets (reanalysis models, bias-correction technique, and target datasets; from the priority 2.1 "Climate Track" simulations);
3. A summary of Phase 1 results for priority 2 crops (from the priority 2.2 "Crops Track" simulations).
4. A detailed assessment of all national- and continental-scale extreme climate events in the historical record, and the ability of models to reproduce the agricultural impacts of these events.
5. Sensitivity of simulated crop yields to the ET0 equation used within the crop model, which has been identified as a priority model process difference to evaluate and understand in Phase I. Preliminary results, obtained using pDSSAT run with both Penman-Monteith and Priestley-Taylor ET equations, show a difference in simulated yield up to 30% in some regions (most notably in rainfed systems in arid regions.
6. Variability from models, weather, over the historical period.

We will submit at least two of these publications to top tier general-interest science journals (e.g. Science, Nature, NCC, etc.) and expect other submissions to more technical high-level general science journals (such as PNAS, Nature Communications, etc.).

C3MP Work Group Report

Alex Ruane and Sonali McDermid

• Brief lay-person-oriented description of work group activities

The Coordinated-Climate Crop Modeling Project (C3MP) organizes crop modelers from around the world to investigate how agriculture will respond to climate changes. Experts at more than 1000 locally-calibrated sites from around the world have contributed results to enable detailed study of how changes in rainfall, temperatures, and carbon dioxide concentrations will affect agricultural systems in the coming decades.

• Scientific Issues

Understanding the response of different crops, models, and locations to changes in mean carbon dioxide concentration, temperature, and water (CTW). How can we assess the quality of this response and the minimum requirements for comparison of two simulation sets? What is the density (or number of sites with a common characteristic) required to perform more comprehensive analyses (e.g., of a broader region, crop, or crop model)? How consistent are the CTW responses?

• Group Activities and Protocols Underway

C3MP has an established and simple protocol. The overall project is relatively simple, however:

1) the execution of CTW sensitivity tests can be quite arduous for some models
2) the creation of C3MP tools facilitates project execution and results reporting
3) the organization of the project requires detailed planning
4) the distribution of project results must be carefully controlled.

• Near-term Model Improvements

The entire project improves with each further participant and simulation set that expands the C3MP network; therefore we are looking for more crops, crop models, and locations. We would be grateful for more assistance in the creation of IT tools to facilitate the generation of C3MP scenarios, which would facilitate and encourage additional participants. Dominique indicated that this could easily be done for STICS model users. As groups are successful for particular models we need to capture and tools or procedures they created in order to assist future participants with the same model.

• Next-Generation Components

Future C3MP initiatives would be improved by the inclusion of a closer look at climate variability metrics (e.g., a monsoon-oriented set of sensitivity tests for South Asia, SE Asia, and/or West Africa), devoted analysis of nitrogen interactions, and capacity for harmonized archives of C3MP results from gridded crop models. Submissions planned for grasslands and livestock production. Pests and diseases also respond to CTW changes, so sensitivity tests would be appropriate way of developing damage functions that could inform AgMIP simulations and analyses.

• Priorities for Integration across Disciplines

Already have strong climate and crop modeling participation. Would like to pursue connections to economics modeling, e.g., simple yield change factors for TOA or integrated assessment modeling.

• Contributions to Regional/Global Scale Interactions

C3MP has the potential to bridge scales as a dataset that spans a large area and a large number of crops, but where each site was individually calibrated. Results may thus be used to compare against GGCMI simulations from AgGRID, against model results and experimental data at crop model pilot sites, and against the directly simulated scenarios in AgMIP's Regional Integrated Assessments. As the density of C3MP results increases, there may eventually be the ability to aggregate up to national (and potentially higher) scales.

• Timeline for Coming Year

December 31st, 2013 = Next submission deadline

January – December, 2014 = Archives still open for submission; results only available to those who have contributed results

January 1st, 2015 = Outputs publically available

• Planned Publications

1) Working Title: C3MP Protocols and Archive

Authors: Sonali McDermid (sps2113@columbia.edu) and ALL C3MP Participants

2) Working Title: Global Climate Impacts
Authors: Alex Ruane (alexander.c.ruane@nasa.gov), and ALL C3MP Participants

3) Working Title: C3MP Projections for Argentina
Authors: Gabriel Rodriguez (garodri@gmail.com) and Guillermo Garcia

4) Working Title: C3MP Wheat
Authors: Senthold Asseng (sasseng@ufl.edu) and participants who submitted wheat data

5) Working Title: C3MP Rice
Authors: Participants who submitted rice data

6) Working Title: C3MP Maize
Authors: Participants who submitted maize data

7) Working Title: C3MP Sorghum
Authors: Flavio Justino, KPC Rao (?) and participants who submitted sorghum data

8) Working Title: Comparison of AgMERRA and local weather data for C3MP results
Authors: Alex Ruane (alexander.c.ruane@nasa.gov) and participants who submitted both datasets

9) Working Title: Comparison between DSSAT 4.5 and DSSAT 3.0
Authors: Richard Goldberg

10) Working Title: Patterns of global agro-climatic sensitivity
Authors: Sonali McDermid (sps2113@columbia.edu), Alex Ruane, and Nick Hudson

11) Working Title: Comparison of C3MP and GGCMI results
Authors: Alex Ruane (alexander.c.ruane@nasa.gov), Joshua Elliott, and Sonali McDermid

12) Working Title: Forms and fidelity of C3MP Emulators
Authors: tbd

13) Working Title: CTW responses for Bambara Groundnut
Authors: Asha Karunaratne

14) Working Title: Uncertainty in CTW Impacts Response across the C3MP Network (broad audience)
Authors: tbd and ALL C3MP Participants

15) Working Title: CORDEX and Global Model Impacts
Authors: tbd

16) Working Title: Differentiating climate impacts on worst years versus average years
Authors: tbd

Funding Requirements
C3MP is currently unfunded, but support for coordination and IT development would be beneficial

Crop Modeling Work Group Report

Peter Thorburn and Ken Boote

- **Scientific Issues**

Crop models have been developed to capture the effects of how crops respond to the environmental factors they experience during their growth. The concepts and algorithms in the models have largely been drawn for the responses measured in field experiments. Those experiments have been conducted in the past and so necessarily reflect the climate and atmospheric conditions of the past. As these conditions vary in the future through global climate change, there is well-founded concern that the model predictions may not be accurate for future climates. Thus, these models may not be providing accurate indications of crop growth and food supply in the future.

In addition to this uncertainty about the validity of mechanisms within crop models under future climatic conditions, the models differ in their structure, parameterization, etc. These differences reflect the uncertainty within the crop modeling community about the understanding of these processes and how they are best represented in models. So, this uncertainty is inherent in all predictions, but not revealed in

simulations coming from a single model. Therefore, making predictions with an ensemble of models offers an improvement and way to reduce overall uncertainty.

• Group Activities and Protocols Underway

Crop model intercomparison and improvement groups currently established include

- Wheat
- Maize
- Maize model improvement group
- Rice
- Sugarcane
- Soils

These groups have commenced activities and have produced outputs ranging from preliminary intercomparison data (soils and maize improvement) to papers submitted or published (all other groups).

New groups that have been formed, but have yet to produce outputs are:

- Potato
- Sorghum
- Groundnut
- Cassava

There are also plans to establish new working groups to address important issue that have emerged from the AgMIP community over the past year. These groups will address:

- Canola/rape seed (contact: Enli Wang)
- Biofuel crops (contact: Gopal Kakani)
- Crop-water-use and ET team (contact: Jerry Hatfield)

• Near-term Model Improvements

It is important to note that improvements will be driven by comparison with data.

The wheat model improvement group is in the process of assessing the performance of 28 different models in simulating effects of high temperature, the factor determined to be the highest priority for improvement. This group has a methodology for modeling teams to test the improvements against data from the Hot Serial Cereal experiments. It is likely that improved wheat models will evolved during 2014, as the modelers modify code and parameterization to improve wheat model response to temperature. A sub-group will also test models from AgFACE data from Australia (O'Leary et al.).

The rice model improvement group is focusing on CO2 responses, using data from FACE experiments in Japan and China. There is also a planned activity in the near future looking at improving temperature responses by testing against elevated temperature response observations.

The maize crop intercomparison group is aiming to evaluate growth and ET at elevated CO2 against data from FACE experiments in Germany and USA. The maize model improvement group (MMIG) is developing a new model called AgMaize with improved phenology, leaf area expansion, leaf-canopy assimilation and partitioning.

The sugarcane improvement group has gathered data from a wide array of environments, and these data will allow a partial space-time analysis for water and temperature stress that will provide the basis for model improvement. Glasshouse experiments have recently been conducted on CO2 response, and the models will have their CO2 response functions updated accordingly.

• Next-Generation Components

The highest priority next generation components are to develop models better equipped to represent effects of extreme elevated temperature, water stress and CO2 concentration. Our modeling of these processes is, in reality, data constrained.

Representing other processes important in climate change impact, but not included in current models, is likely to be even more constrained by data. Detailed interactions between the crop modeling community and process scientists in these areas will be required to make progress. These other processes will include, but not be limited to, effects of ozone on crop growth, pests and diseases, soil drainage, crop submergence, water logging, salinity and grain quality. The magnitude of the effort to incorporate these processes into crop models accurately should not be underestimated. Having said that, some models do have capacity to represent some of these processes, to greater or lesser

extent (e.g. APSIM and RZWQM modeling tile drainage, APSIM's link with Dymex to model pests in grains) that may provide examples for other modeling groups.

• Priorities for Integration across Disciplines

Good to explore links with the following global communities:

- Good potential links to Global Energy and Water Cycle Experiment (GEWEX :http://www.gewex.org/) for insights into ET.
- Remote sensing community for information on ET, canopy development, etc.

There are plans to establish a new working group to address the important issue of crop water use-ET (contact: Jerry Hatfield) because model intercomparisons show large variation in predicted ET and transpiration across models. The crop water-use-ET team will work across crops, across site-specific models, and across global modeling communities to test their models against available ET-crop-water-use data. The links to global communities (e.g., GEWEX, remote sensing and experimentalists) will be especially important to the Crop water use-ET group.

Another important issue to emerge during the Global Workshop was the need for stronger interactions between the crop modelers and the economists to discuss RAPS. The priority for these discussions is the representation of adaptation, such as changed management, genetic improvement and socio economic constraints. Integrated assessment activities need to place a higher priority on simulating adaptations.

• Contributions to Regional/Global Scale Interactions

Discussions of regional/global scale interactions identified a number of potentially useful interactions, such as:

- What does a grid represent?
- Sensitivity analyses of predictions for a grid that contains good point simulations, such as comparing relative sensitivity of the global model against point data (as in ET).
- How do we parameterize cultivars?

These ideas will only be better developed through detailed interactions between the members of the crop and gridded modeling communities.

• Timeline for Coming Year

Time lines are either given above or available through work plans for the individual improvement groups.

Plans for publications

- Wheat: Eight papers under consideration, ranging from recent submission (PNAS) to concept development.
- Maize: One paper submitted (GCB), and one (on ET) in the pipeline.
- Maize improvement; < 4 in the pipeline
- Rice: One submitted (PRS London) and two in process
- Sugarcane: One paper submitted (EM&S).
- Biofuels: Several papers are being published on the development of biofuel crop models.

• Funding Requirements

US$150,000/yr per Group to undertake meaningful work in a timely manner. So the ten Groups in existence imply an investment of US$1.5M/yr.

• Brief lay-person-oriented description of work group activities

Much of our knowledge of crop production and food security come from our past experience. As the climate changes in the future, this experience will become less relevant and there will be increasing uncertainty about the extent to which agriculture will be able to meet food demands for an expanding population.

This activity will improve simulation models of crop production so they are better tools for assessing future food supply. In addition, it will develop and demonstrate methods for more explicitly representing the uncertainty in these assessments, so that they provide a more robust and higher quality evidence base to inform policy discussions on future food security at local, regional and/or global scales.

Global Economic Modeling Work Group Report

- **Scientific Issues**
  - Model comparison – improve understanding of the sources of differences between the global economic model results
  - How to better link global and regional modeling
  - Communicate the results to users

- **Group Activities and Protocols Underway**
  - Compare model results to explicitly specified shocks to elicit arc demand and supply elasticities
  - Develop review paper on land use modeling approaches
  - Participate in regional/global model discussions in EU, US, and Canada, and others as opportunities arise
  - See RAPs discussion

- **Near-term Model Improvements**
  Shorten time steps

- **Next-Generation Components**
  Incorporate uncertainty. This is a 3 year effort.

- **Priorities for Integration across Disciplines**
  Better integration with global gridded crop models

- **Contributions to Regional/Global Scale Interactions**
  See above

- **Timeline for Coming Year**
  Complete shocks experiment and land use modeling review paper

- **Funding Requirements for one year**
  $500,000

- **Brief lay-person-oriented description of work group activities**
  Policy makers need simple metrics of model performance as well as straight forward explanations of key model results. The shock experiment will generate metrics that are familiar to agricultural policy makers. The land use review paper will expand on the Agricultural Economics paper on land use to a more in-depth assessment of model specific methods of quantify land use expansion potential.

Grasslands & Livestock Report

Lead: Jean-François Soussana, INRA, France.

- **Scientific Issues**

Figure 1. Organisation of the grasslands and livestock group

We have expanded the scope of activities by including livestock modeling activities (initially, cattle only). Hence, there are two pillars corresponding to grasslands and to livestock. In each pillar, we plan the following activities (model sensitivity climate, intercomparison with blind tests, model calibration and further intercomparison, site based model projections). While the two pillars can be seen as partly decoupled activities, some models simulate in a coupled way pastures and livestock. Moreover, indirect coupling could be developed (e.g. simulating herbage production and herbage digestion by ruminants) (Fig. 1).

- **Group Activities and Protocols Underway**

Grasslands

Sensitivity analysis, contributing to C3MP

Sensitivity will be first assessed with models that have been calibrated/evaluated at high quality sentinel sites and that meet the AgMIP requirements (see Annex 1 for groups

agreeing to contribute). This will be organized as a grasslands contribution to C3MP (see workflow below). We agreed on three broad grassland categories: temperate, tropical, rangelands.

For each category, we have a subset of modeling groups. We will ask each group to report on their model and their site (model and site templates) and to provide 31 yrs weather data complying with C3MP standards. We will then use the C3MP procedures for generating the modified weather products that will allow to run the CO2*T*P hypercube for each site/model pair. The detailed outputs will be processed by the Grasslands activity and simpler production outputs will be reported to C3MP. The IT team will provide support (translators, raw data formats, data archives). We will ask groups to report on sites used for models calibration/evaluation and also on high quality datasets that can be used for sentinel sites.

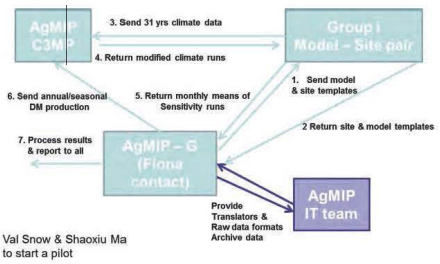


Figure 2. Provisional workflow for the grasslands sensitivity analysis

We agreed on data outputs and on the theoretical management assumed in each site for this sensitivity analysis:

Theoretical grassland management. Assume cuts every two weeks (on 1 and 15 of each month of each year). Cuts will be effective whenever the biomass is sufficient. The reason for applying such a cutting procedure is that large changes in climatic conditions resulting in herbage accumulation changes would require adaptations in grazing (e.g. stocking density) that are site specific and that will confound the sensitivity. Fertilization needs to be kept constant across the climate conditions and to be adapted to the nutrients exports resulting from cuts. Note that an alternative would be to have short grazing events every two weeks, but this seemed more difficult to standardize.

Output variables. NPP (GPP), harvested DM, mean above-ground DM, mean below-ground DM, mean LAI, mean harvested (N content, digestibility, NDF), total SOC stock (annual to 30 cm and to total soil depth), N2O (and total denitrification if possible), soil temperature in 0-30 cm, soil moisture in 0-30 and in total depth, real evapotranspiration. A preliminary step will be to populate a table with models times output variables. All output variables will be reported as monthly means.

Formats. We are exploring the format standards with the IT team. While there is a medium term need for standardization of vocabulary, development of further translators (etc…), we will base our initial effort on formats adapted from those used by the crop teams.

Publication plans. We anticipate a paper focused on the climate sensitivity of grassland models and a contribution to the broader C3MP paper. Depending on results, other papers could be prepared.

- **Grassland model intercomparison and benchmarking**

Based on their description and applicability, models (see Annex 1) will be allocated to one or several of the three grassland types (temperate, tropical, rangelands). In the sensitivity step, models performances were reported for a theoretical management at a site for which the model has been calibrated. We therefore have in each grassland category, a subset of models/site pairs.

Site selection. Following the general principles of the silver/gold/platinum classification, the best sites will be delineated in each grassland category. We expect to have at least three high quality sites on different continents in each category. The input data (climate, vegetation, herd, soil, management,…) will be reported for those sites to the coordinating team and their formats standardized. Moreover, key data for model benchmarking (see provisional list, Table 1) will also be send to the coordinating team and will be processed according to a standard template.

Blind test In each grassland category, each model will be run for each site based only on the input data send in the standard format to each site. Some site-specific parameter

values may be adapted by model teams, based on their expertise. Details of this procedure will be discussed with the wheat and maize pilots to benefit from their experience. The blind test model outputs will be reported in the standard format (using monthly values?).

- **Model intercomparison and benchmarking workshop**

This workshop will take place on March 20-21, 2014 in Paris. It will be organized jointly with the C-N group of the Global Research Alliance (GRA) on agricultural greenhouse gases, to take advantage of the synergies between the two activities (within GRA, models are used for GHG emissions estimates and for tests of mitigation options). In this workshop, the first results of the blind test will be reported and discussed, the use of the mean of an ensemble of models will be evaluated and further steps will be planned. We anticipate to run a second intercomparison after calibration, plus a parameter permutation exercise (in order to test the role of changes in parameter values).

- **Near-term model improvements and next generation components**

In the near term, we will concentrate on the sensitivity and intercomparison/benchmarking steps. From the understanding gained, we plan for model improvements focusing on the following areas which were identified as sources of large uncertainties:

i) Response of vegetation and soil to climate (T, P, CO2) with focus on extreme events. This would be organized through a questionnaire to have modelers report on the functions used. Links with ecosystem manipulation experimental data will be organized to improve parametrisation.

ii) Herbage quality. Key variables (N content, digestibility, NDF…) will be evaluated and discussed and improvements considered.

iii) Plant functional types composition and dynamics. A review of the models will be organized and discussions initiated.

Based on these discussions, we will encourage modelers to run model improvements. This may, however, targeted funding. The next generation component that we foresee concerns the 'climate proofed pasture models, including grazing management and GHG balance' (CPPM..).

Contributions to Regional/Global Scale Interactions

We have three DGVMs

MODEL	CONTACT	COMMENT
ORCHIDEE	Viovy, Nicolas (FR)	C3/C4 grass, management
LPJml	Rolinski, Suzanne PIK	Temperate
Biome BGC	Montana U. (tbc)	

These have plant functional types, including C3 and C4 grasses and some (e.g. Orchidee new version) have grazing management. These models will be part of the intercomparison and will benefit from the activities in the group. Collaborations on grazing management, on diet quality etc… could be further developed. Other integrated models (e.g. GLOBIOM) have EPIC which is also part of the grassland intercomparison. Gridded applications of pasture models could help in proposing bias corrections in the main DGVMs and integrated models. In 2014, we anticipate to start the first discussions on this issue.

- **Timeline for Coming Year**

End 2013. Send model and site templates.
Collect weather data.

December 2014. Send the blind test input data.

January 2014. Process the hypercube.

Early 2014. Send the modified weather data to model groups. Deadline for model runs: end February 2014.

March 2014. Benchmarking and intercomparison workshop.

May-September 2014. Data analysis from blind test and from intercomparison.

- **Housekeeping**

A collaborative space and a server space will be organized for the activity.

- **Funding Requirements**

100,000 $ per year would be required.

We hope at least some support for travel of groups participating, especially from developing countries. Support from IT team and from C3MP will be critical for the success of the activities.

• Brief lay-person-oriented description of work group activities

Pastures and livestock are critical aspects in both low-intensity and high-intensity agricultural systems and how such systems are likely to respond to climate change. These systems will also play an important role in the mitigation of GHG emissions. As regional and global impact assessments are undertaken it is important that we have confidence in the performance of the models that simulate pastures and animals and their integration into cropping systems. This workgroup will undertake activities to benchmark models simulating pasture and animal performance under a wide range of environments - from cool-temperate to tropical to rangeland conditions. The benchmarking exercise and the data used in the benchmarking will be used to improve the models and then we will use the ensemble of models applied to high-quality datasets to quantify the uncertainty of our predictions of pasture and animal performance under current and possible future conditions. The information will be used to inform or improve the models used in global gridded assessments and to inform assessments of the impact of climate change on individual farms and households.

Annex 1. Provisional list of models contributing to the intercomparison, benchmarking and sensitivity analysis. Data provision is still being explored.

MODEL	CONTACT	COMMENT	Available data
CENTURY, DAYCENT / SAVANNA	Conant Rich (USA)	Grasslands / Rangelands	YES
GPFARM-Range	Ahuja, Laj (USA)	Rangelands	
	Samuel Adiku (Ghana)	Savannah rangeland	
FASSET, FARMGHG	Olesen, Joergen E (DK)	Temperate grassland	
LINGRA, LPJ Grass	van Itersum, Martin (NL)	Temperate grassland	
STICS Grassland	Ruget, Francoise (FR)	Temperate grassland	
PROGRASS	Calanca, Pier Luigi (CH)	Temperate grassland	
PASIM, FARMSIM	Bellocchi, G; Soussana, J-F (FR)	Temperate (field/farm)	YES
TOA-MD	Antle, John (USA)	Temperate grassl/rangel.	
EPIC	Roggero, PP (IT)	Temperate/Tropical	YES
APSIM-GRAZPLAN/AgPasture	Moore, Andrew (AU), Val Snow (NZ)	Temperate/Tropical	YES
DAIRYMOD/ECOMOD	Cullen Brendon (AU/NZ)	Temperate/Tropical	
CROPGRO	Boote, Ken (USA)	Tropical	
APSIM - APSFARM	Masikati, Patricia (CGIAR)	Tropical	
GRASSIM	van Itersum, Martin (NL), Descheemaeker, Katrien (NL)	Tropical (semi-arid, savanna)	YES
Phygrow/APEX/EPIC	Jay Angerer (USA)	Tropical, Savannah, Temperate	
SAVANNA/QuD	Greg Kiker	Savannah (Kruger Park)	
G-Range, Ruminant	Herrero, Mario (CSIRO)	Tropical grassl./rangel.	

Aggregation / Scaling and Uncertainty Work Group Report

Antle, John; Ewert, Frank; Hoffmann, Holger; Mearns, Linda; Wallach, Daniel

• Scientific Issues

From the scaling point of view, the main issues involve the identification and quantification of influences of scaling methods (e.g. sampling and aggregation) on model performance and representativeness. The aim of the scaling activities in AgMIP is to identify and quantify strategies applicable for crop model upscaling. Methods are developed in order to extract characteristic model sensitivities and optimal sampling and aggregation strategies. The approaches include the evaluation of crop model uncertainty on the multi-model level at local and regional scale in order to deduct general conclusions for upscaling applicable across regions and models including model ensembles.

The three main scientific issues concerning uncertainty are how to characterize the uncertainty (e.g., do we know the source and understand it?), how to quantify the uncertainty for different responses at different scales, and how to apportion overall uncertainty to specific causes.

Further research topics addressed are:

Quantification of sources of uncertainty using comparisons with observed regional and subregional yield.

Uncertainty in impact assessment

Quantification / Estimation of the fraction of uncertainty in crop models which is ignored (effects of weeds, diseases, pests, ozone, other) , compared to the fraction which is known / considered.

Evaluation of crop model uncertainty based on ensembles (of crop models). (Profiting from the experience with climate models, e.g., use of model weighting).

Model calibration as a source of model uncertainty

Effect of internal climate model variability on impact assessment

Climate uncertainty vs. crop model uncertainty as function of time horizon, e.g. estimating the time of emergence (ToE) / significant horizon (see Hawkins & Sutton 2009, Hoffman & Rath 2013).

• Group Activities and Protocols Underway

A regional multi-model scaling study (1st regional scaling) with stratified sampling for different numbers of sampling points has been conducted in order to investigate optimum sampling strategies and the contribution of sampling to the simulation error / uncertainty. All groups contributed their single model runs to the ensemble of potential and water limited yield of winter wheat. First results are presented and ongoing evaluation and uncertainty analysis discussed. Next steps will increase the level of spatial heterogeneity by including soil information.

In order to set up / investigate effects in ensemble runs, the range of methodological approaches known from climatology (e.g. Hawkins & Sutton 2009) will be tested. Parameter and structural uncertainty of crop models will be separated by the example of phenology / phenological model compartments.

A draft white paper on uncertainty has been circulated, and will serve as the basis for further discussions concerning uncertainty. All AgMIP participants are encouraged to provide comments on the draft.

• Near-term Model Improvements

Optimum sampling / contribution of sampling to regional model performance will be included in future model simulations.

• Next-Generation Components

Optimal sampling strategies with regard to spatial variability, model characteristics and interaction of scale and model, possibly extended for model ensembles.
Comparison of methods of estimating uncertainty based on ensembles, and establishing improvements in methods.
Estimation of uncertainty in impact analysis.

• Priorities for Integration across Disciplines

The investigated issues are general and therefore applicable to most model types. Optimum scaling and sampling are prerequisites for simulations whereas analysis of uncertainty propagation is interdisciplinary per se.

Propagation of uncertainties in crop model outputs to economic models.

- **Contributions to Regional/Global Scale Interactions**

Scaling crop model simulations to a spatial aggregation level that is usable for economic models.

- **Timeline for Coming Year**

2014: Regional scaling exercise with increased complexity
2014: Case study separating parameter and structural crop model uncertainty
2014: Identification and set up of climatological uncertainty analysis methods which are potentially applicable to ensembles of climate-crop-socio-economic model chains (review).
2014: Study on application of lessons from climate modeling to ensemble-based uncertainty for crop models.

- **Funding Requirements**

PhD for extending scaling exercise to other region(s) in Africa and crop(s) (e.g. Nigeria, e.g. Millet) and for linking upscale model results with economic models.
Uncertainty postdoc to work on the full range of uncertainty research topics. Partial support for programmer if large data set manipulation is required.

- **Brief lay-person-oriented description of work group activities**

The first goal of this group is to develop methods for simulating yields at the level of a region, based on simulations for individual fields. Studies are being carried out to test and evaluate various methods. These studies involve multiple modeling groups.

The second goal is to characterize and quantify uncertainty in simulated responses. A draft white paper has been distributed, and will be the basis of discussions among a large community of researchers interested in this area. The white paper has a broad discussion of the sources of uncertainty and the way uncertainty is evaluated, the contribution of AgMIP to the methodology of evaluating uncertainty in crop models, ag-economic models, the details of current uncertainty analysis in AgMIP and finally proposals for future AgMIP research and for the organization of this theme in AgMIP.

- **Publications**

Two paper on the scaling exercise (phase 1, one in 2013, one in 2014).

Three + X papers on the scaling exercise (phase 2, 2014) are planned.

A draft white paper on uncertainty has been circulated, and will serve as the basis for further discussions concerning uncertainty.

One paper on the application of lessons from climate modeling to ensemble-based uncertainty for crop models (and possibly ag-economic models).

Soil and Crop Rotation Work Group Report

Bruno Basso and Angela Kong

- **Scientific Issues**

Typically climate change impacts on crop yields are simulated with an approach that re-initializes soil conditions to the same state each year. If simulations neglect to include year-to-year changes in soil conditions related to agronomic management (soil organic carbon, soil nitrogen, soil water content), adaptation and mitigation strategies designed to maintain stable yields under climate change cannot be properly evaluated, thus re-initialization of initial conditions as per status quo is not appropriate.

In a recent meta-analysis of CERES models applied to measured data on maize, wheat and rice, Basso and Liu (2014) found that CERES models have been extensively tested for yields or biomass (over 120 papers), but their validation for soil water balance (20 papers), carbon and nitrogen cycling in agricultural systems has been limited (only 8 papers). It is rather clear that crop models need to include soil parameters as proper initial conditions to produce realistic simulations of grain yield by capturing the legacy effects of soil carbon, nitrogen and water from the off-season on the next growing season. The Soil and Crop Rotation Work Group is comparing the results of sequential simulation (continuous runs without resetting initial conditions) of different models on soil variables (e.g., soil organic carbon and nitrogen, water balance, and later greenhouse gas emis-

sions). In the context of climate change, if adaptation and mitigation strategies are to be identified, then changes in soil conditions over time need to be accounted for.

• Group Activities and Protocols Underway

Since mid-2013, the AgMIP Soil and Crop Rotation Work Group has been engaged with Phase I simulations of the wheat and maize pilot sites using continuous simulations. The objectives of Phase I are to: i) assess crop model uncertainties in simulating soil carbon, nitrogen and soil water balance dynamics in a maize - fallow and wheat - fallow crop rotation under different management strategies in a sequential mode for 30 continuous years (historical (1981-2010) and future climate projections (2011 -2040)) using different management strategies and crop rotation, and ii) to compare yields simulated using the prior method of constant reinitialized soil parameters used in the wheat and maize pilot studies accounting for legacy effects of soil water, carbon and nitrogen obtained by running the model in the sequential mode. Protocols and data sets to be used in Phase I simulations can be found at http://www.agmip.org/soils. The sites selected to be used in Phase I are identical to those used in the wheat pilot (Australia, Netherlands, Argentina and India) and maize pilot studies (USA, France, Brazil, and Tanzania).

In Phase II (see timeline below), the Soil and Crop Rotation Work Group will follow up Phase I with model tests at long-term sites (ideally at least 20 years) that have more detailed soil carbon, nitrogen and water data. Another objective of Phase II is to evaluate how the models cope with sites with low availability of input, e.g., sentinels copper sites like chrono-sequence sites in western Kenya.

• Near-term Model Improvements:

With Phase I model runs currently underway, there are few near-term model improvements proposed at this stage. Model improvements will depend on the performance of the initial pilot results. Expected limitations may deal with the way different models handle soil organic carbon and nitrogen mineralization rates. Improvements will be made to models if soil fertility impact on yield is not properly captured.

• Next-Generation Components

The next-generation models should incorporate salinity, excess soil water and drought and greenhouse gas emissions in order to properly identify adaptation and mitigation strategies when these issues are predominant. The Soil and Crop Rotation Work Group will also focus on developing better transferability of the models and reducing the sensitivity of models to limited inputs (e.g., sentinel copper sites).

• Priorities for Integration across Disciplines

Modeling of soils processes (soil fertility, available water, soil quality/degradation) must be included in every crop modeling exercise that aims at modeling long-term impact of management strategies and climate change on crop yield. The AgMIP Soil and Crop Rotation Work Group plans to be in close contact with the crop the Crop and Livestock teams, as well as the Regional Groups working on integrated assessment.

• Contributions to Regional/Global Scale Interactions

It is pertinent that crop modeling at the regional/global scale includes properly initialized soil conditions in order to accurately model yields as well as carbon, nitrogen and water fluxes. In order to scale up from the field level, a spatial component is necessary. FAO and UNESCO, along with the Digital Soil Mapping initiative will cover an important role on providing existing information on soil maps which can be used to scale up from field to Region.

• Timeline for Coming Year

The AgMIP Soil and Crop Rotation Work group is currently engaged in Phase I simulations (described above). The group will complete Phase I by the end of 2013 and synthesize the results into a publication in 2014. Phase II, which will include new sites and more data measurements, will begin in the Spring of 2014.

• Funding Requirements

a. Pursue funding for workshop and travel funds to Global Workshop

b. Funding for core person (programmer/post-doc) to support this initiative/work group in compiling and analyzing data from all the groups.

• Brief lay-person-oriented description of work group activities

Soils are the backbone of agro-ecosystem function and productivity. Therefore, it is pertinent to include soil compo-

nents into simulations of management scenarios to identify best management practices under current and future climate. Crop models generally re-initialize soil conditions, which might suffice when looking at climate variability; however, this approach suffers from not taking into account legacy effects of soil carbon, nitrogen, and water content. The primary aim of the AgMIP Soil and Crop Rotation Work Group is to account for changes in soil conditions over time (e.g., soil carbon and nitrogen and water balance) in order to accurately model crop yields at sites covering a range of data richness as well as identify adaptation and mitigation strategies.

• Planned Publications

AgMIP Soil and Crop Rotation Work Group plans to publish the results of Phase I and II in highly ranked journals including as co-authors, AgMIP leaders, data providers and scientists participating in the initiative.

Water Work Group Report

• Participants

Jonathan (Dartmouth College), Francisco Meza (Catholic University of Chile), Tom Gerik (Texas A&M), Daniel Hillel (Columbia University), Arthur Gueneau (International Food Policy Research Institute), Arthur Greene (International Research Institute for Climate and Society), Forrest Melton (Cal State Monterey Bay, NASA Water Resources Program), Vijay Nazareth (University of Florida), Christine Lee (AAAS Fellow, NASA Water Resources Program), Greg Kiker (University of Florida), Rafa Muñoz-Carpena (University of Florida), Liqiang Sun (North Carolina State University), Stefan Niemeyer (European Commission Joint Research Centre)

• Scientific Issues

The three key scientific issues discussed were: efficiently linking available water for irrigation to agricultural assessments, the representation of evapotranspiration (ET) and other hydrological fluxes in crop models, and scaling hydrologic and crop model output to decision-relevant (river basin, regional, national, global) levels. In addition, the group also discussed a variety of topics, including: timing of limited irrigation, water infrastructure and management, water competition from other sectors, supply allocation, salinity and quality, groundwater and drainage, non-stationary supplies (snow, glaciers), how to interface with decision makers and stakeholders (e.g., AgMIP crop and economic modelers, regional water managers, agencies, ministries), the use of station and remote sensing data to constrain hydrologic and crop models (e.g., SMAP, SWOT reservoir height, Landsat 8 ET, GRACE groundwater), hydrometeorological extremes, linkages between water, agriculture and energy, policy, including boundaries and compacts.

• Group Activities and Protocols Underway

The only explicit AgMIP Water activity is continuing collaborations from the AgMIP-ERS Water Workshop, which was held in April 2013. However, there are multiple relevant projects being pursued by AgMIP-related investigators at various stage of integration with AgMIP efforts, including: WEAP-DSSAT Central Valley project (Winter), WEAP-CropSYST in Chile (Meza), SWAT across the US and world (Gerik), construction of drought scenarios (Greene), IFPRI IMPACT water model integration (Gueneau), Costa Rican QnD watershed management (Muñoz-Carpena and Kiker), ET estimation and irrigation management in the Central Valley (Melton), combining LISFLOOD, BIOMA, and CAPRI (JRC). The group felt that given the early stage of AgMIP Water, detailed, official, protocols were not necessary and it would be best to instead rely on open communication and collaboration to encourage informal protocols.

• Near-term Model Improvements

The discussion focused more on potential projects as opposed to model improvements. Potential priorities for AgMIP Water included: develop the best (comprehensive and efficient) way to integrate crop and hydrologic models, interface with ISI-MIP Water and GGCMI, map global crop water stress frequency indicators, participate in the development of RAPs, establish geographic regions of interest to build efforts. Other projects proposed were: assess uncertainty in water resources supplies of global models vs. catchment models, improve crop and hydrologic models by extracting information hydrologic models can provide to crop models and vice versa, create a platform for coupling hydrologic and crop models, further scenario approaches to water resources assessments, focus on places and times of urgency, assess the vulnerability of areas dependent on groundwater, evaluate non-renewable water supplies (groundwater, glaciers, etc.), explore what global agriculture (yields and prices) would look like without groundwa-

ter, advance projections of water use and distributions, provide water database for crop modelers in collaboration with the IT group.

• Next-Generation Components

The group identified the following longer term goals: modularize hydrologic and crop models to enable greater ensembles leveraging more model combinations, develop and implement a range of water use projections and distribution scenarios, explicitly integrate groundwater, develop close partnerships between AgMIP Water, ISI-MIP Water, and AgGRID, assess water excess impacts, evaluate salinity and other water quality issues.

• Priorities for Integration across Disciplines

The priorities for integration across disciplines discussed by the group included: economics - yields, energy, link water use and distributions to RAPs; crops - irrigation water supply, flooding, water logging, run-on, transpiration, deep percolation, recharge, water demand, runoff, water conservation practices, crop management, irrigation scheduling; pests and diseases - water-dependent pests, diseases, and processes; livestock - flooding, water demand, water quality; climate - temperature and precipitation forcings.

• Contributions to Regional/Global Scale Interactions

The key contribution of AgMIP Water to regional and global scale interactions is to provide consistent water constraints on agriculture. The group felt that it was too early to discuss this contribution in further detail.

• Timeline for Coming Year

The timeline agreed upon by the group was: Next AgMIP Water Workshop – Start immediately, target July/August 2014. Funding Possibilities: NASA E.2, NSF, NIFA, USDA International Programs, EPA, EU sources. Submit Manuscript – Start immediately, target Fall 2014. Review and proof-of-concept manuscript submitted as a group. Working title: "On the Need for Hydrological Linkages in Crop Modeling". Collaborations - Team members will continue to work and report progress on their respective "Sentinel Watersheds". Partnerships - Jonathan and other AgMIP Water participants attend ISI-MIP Water meetings.

• Funding Requirements

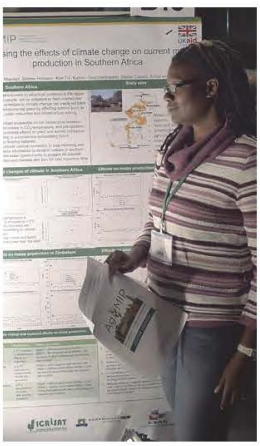
The group thought it was premature to brainstorm funding requirements, so instead discussed possible ways to fund near-term work. This included workshop money potentially from NASA E.2, NSF, NIFA, USDA International Programs, Cotton Growers, EPA, and EU sources. In the short term, projects will be supported by grants obtained by AgMIP-related scientists and leveraging existing AgMIP networks and efforts.

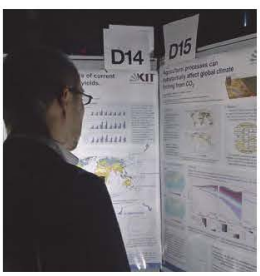
• Brief lay-person-oriented description of work group activities

Understanding evolving water resources, such as changing precipitation patterns, decreasing groundwater supplies, and growing water use, is a key component of determining climate impacts on agriculture. During the AgMIP Global Workshop a group of researchers convened over a series of breakouts to start the process of organizing an AgMIP research effort to improve the representation of water supply and demand in assessments of the agricultural sector. The breakouts started by brainstorming relevant methods, datasets, and currently existing projects. The conversation then transitioned to identifying ways to develop an AgMIP program on water and agriculture. By the end of the breakouts, the group decided to prioritize the following next steps: organize an AgMIP Water workshop, submit a review and proof-of-concept manuscript on water issues within agriculture, and pursue collaborations with related external programs.

• Planned Publications

Given the early stage of AgMIP Water, the group proposed a review and proof-of-concept manuscript: On the Need for Hydrological Linkages in Crop Modeling". The group noted that it would potentially be helpful for AgMIP to organize a special issue that could host a variety of these papers.





POSTERS

See Appendix A for Abstracts

Estimating Impact Assessment and Adaptation Strategies under Climate Change Scenarios for Crops at EU27 Scale, M. Donatelli et al.

Assessing Climatic Risk in Rice Productivity Using Integrated Climate, Crop and Economic Modeling Techniques, A. Ahmad et al.

Global Crop Yield Reductions due to Surface Ozone Exposure: Crop Production Losses and Economic Damage in 2000 and 2030 under Two Future Scenarios of Ozone Pollution, Shiri Avnery et al.

Improving Global Agricultural Production by Mitigating Ozone Damages to Crops via Methane Emission Controls and Ozone Resistant Cultivar Selection, Shiri Avnery et al.

Infrared Warming Affects Leaf Gas Exchange and Water Relations of Spring Wheat, G.W. Wall et al.

Economic Impacts of Climate change on farmers in Nioro du Rip, Senegal: An integrated assessment, Hathie, et al.

AgMIP Wheat, Senthold Asseng et al.

AgMIP Water: Integrating Water Scarcity into Future Agricultural Assessments, Jonathan M. Winter et al.

Biophysical and economic constraints on agricultural intensification in global diet scenarios, Thierry Brunelle et al.

Anthropogenic Climate Feedbacks via Changes in Crop Productivity, Andrew D. Jones and William D. Collins

The Influence of Shifting Planting Date on Cereal Grains Production under the Projected Climate Change, Dae-jun Kim et al.

Critical temperature and sensitivity for white immature rice kernels, Yuji Masutomi et al.

A library of software components for plant airborne diseases simulation, S. Bregaglio et al.

Adaptation of a generic fungal plant disease simulator to assess blast disease (Magnaporthe oryzae Cav.) impact on rice grown in temperate conditions,

S. Bregaglio et al.

Modeling insect pest distribution under climate change scenarios, A. Maiorano et al.

Modelling soil borne fungal pathogens of arable crops under climate change, L.M. Manici et al.

Representative Agricultural Pathways and Climate Impact Assessment for Pacific Northwest Agricultural Systems, John Antle et al.

Enhancing Capacities of the AgMIP South Asia Regional Teams through Capacity-Building Workshops and Knowledge-Sharing Platforms, Guntuku Dileepkumar et al.

An Integrated Assessment of Climate Change Impact on Crop Production in the Nioro du Rip Basin of Senegal I: Crop Modelling, D.S. MacCarthy et al.

ORACLE: Opportunities and risks of agrosystems & forests in response to climate, socio-economic and policy changes in France, Nathalie de Noblet-Ducoudré et al.

Impacts of projected climate change scenarios on the production and prices of staple and nutritionally important crops in the Southern Africa: project overview, Y. Beletse et al.

Integrated assessment of impacts of projected climate change on maize production in the Bethlehem District, Free State, South Africa, Y. Beletse et al.

Projecting spring wheat yield changes on the Canadian Prairies: Resolutions of a regional climate model, Budong Qian et al.

An integrated analysis on Austrian agriculture - climate change impacts and adaptation measures, Martin Schönhart et al.

Modeling crop yields and yield gaps in Russia, Ukraine and Kazakhstan under climate change, Friedrich Koch et al.

Agricultural impacts of climate variability and change in Eastern Africa, K.P.C. Rao et al.

Strengthening Simulation Approaches for Understanding, Protecting and Managing Climate Risks in Stress-prone Environments across the Central

and Eastern Indo-Gangetic Basin, Nataraja Subash et al.

Assessing Climate Change Impact on Rice Based Farming Systems in Sri Lanka and Adaptation Strategies using DSSAT and APSIM Models, S.P. Nissanka et al.

Integrated Assessment of Climate Change Impacts on Principle Crops and Farm Household Income in Southern India, Paramasivam Ponnusamy

Integrated assessment of climate change and policy impacts on food security: a case study for protein crop supplies in Austria, Hermine Mitter et al.

Climate change adaptations for crop-livestock systems in semi-arid Zimbabwe, Sabine Homann-Kee Tui et al.

Assessing the effects of climate change on current smallholder-subsistence maize production in Southern Africa, Patricia Masikati et al.

TOA-MD: A New Approach to Assess Climate Change Impacts and Adaptation for Agricultural Households, John Antle et al.

TOA-MD: A Novel Simulation Approach to Multi-Dimensional Impact Assessment, John Antle et al.

Sentinel Site Data for Model Improvement and Application – Definitions and Characterization, K. J. Boote et al.

Need Across-Models-Across-Crops Testing of Evapotranspiration and Crop Water Use Against Data, K. J. Boote et al.

Progress on the Maize Pilot Study, J.I. Lizaso et al.

AgMIP Rice Team Activities, Tao Li et al.

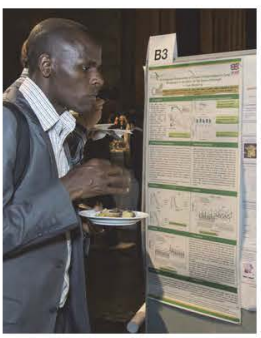
AgMIP Potato Pilot: A summary of progress made, Bruno Condori et al.

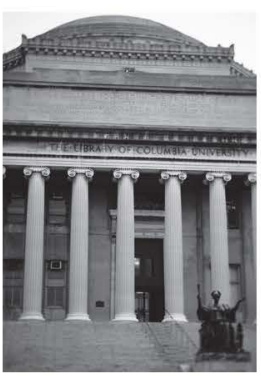
Soil suitability for sustainable intensification in smallholder systems in Sub-Saharan Africa, L. Claessens, et al.

Software frameworks for crop model development and multi-purpose application, A. Topaj et al.

CropBASE: an integrative decision support platform for underutilised crops across research value chains, Asha S. Karunaratne et al.

Modeling the impact of global warming on the sorghum sowing window in distinct climates in Brazil, Flavio Justino et al.





Reimplementation and reuse of the Canegro model: from sugarcane to giant reed, T. Stella et al.

Multi-model simulations for rice yield forecasts in Jiangsu (China), V. Pagani et al.

Simulation of climate change impacts on rice yield and pre-harvest quality in Latin America, G. Cappelli et al.

The Impacts of Climate Change on Rice Farming Systems in North-Western Sri Lanka, L. Zubair et al.

Representative Agricultural Pathways and Scenarios: A Trans-Disciplinary Approach to Agricultural Model Inter-comparison, Improvement and Climate Impact Assessment, John Antle et al.

Development and application of a weather data client for preparation of weather input files to a crop model, Chung-Kuen Lee et al.

Using EPIC for simulating global wheat production: model set-up and future projections, Juraj Balkovi et al.

The Coordinated Climate-Crop Modeling Project (C3MP): Overview and Protocol Evaluation, Sonali McDermid et al.

Climate Impact Estimates on C3MP's Worldwide Network of Crop Modeling Sites, Alex Ruane et al.

The Global Gridded Crop Model Intercomparison (GGCMI), Joshua Elliot et al.

The 2012 AgMIP/ISI-MIP Fast-Track Assessment, Joshua Elliot et al.

Evaluating the utility of dynamical downscaling in large-scale yield assessments, Michael Glotter et al.

Climate scenarios for driving AgMIP models, Arthur Greene

The Extraction of Double-Cropping Areas in North Korea using Fourier Transform

Analysis of Time-series MODIS Imagery, Su-Young Cha et al.

Modelling Efforts and Integrated Regional Studies in FACCE MACSUR, Martin Köchy

Enhancing Model Reuse via Component-Centered Modeling Frameworks: the Vision and Example Realizations, Marcello Donatelli et al.

MODEXTREME - MODelling vegetation response to EXTREMe Events, Gianni Bellocchi et al.

Big Data for Big Solutions: Eddy Flux, Mesonet and C Sequestration, Vijaya Gopal Kakani et al.

A biome-based analysis of current and future global crop yields, T.A.M. Pugh et al.

Agricultural processes can substantially affect global climate forcing from CO2, T.A.M. Pugh et al.

Simulating Adaptive Managagement Using Impact Models in a Risk Framework, Nina K. Pirttioja et al.

Global Crop Yield Reductions due to Surface Ozone Exposure: Crop Production Losses and Economic Damage in 2000 and 2030 under Two Future Scenarios of O3 Pollution, Shiri Avnery et al.

Improving Global Agricultural Production by Mitigating Ozone Damages to Crops via Methane Emission Controls and Ozone Resistant Cultivar Selection, Shiri Avnery et al.

Harmonizing AgMIP Site-Based Data, Porter et al.

PARTICIPANTS

LAST NAME	FIRST NAME	ORGANIZATION
Adamu	James	Nigerian Meteorological Agency
Adiku	Samuel	University of Ghana
Aggarwal	Pramod	CGIAR, Indian Agricultural Research Institute
Ahmad	Ashfaq	University of Agriculture Faisalabad
Ahmad	Shakeel	Bahauddin Zakariya University Multan-Pakistan
Alderman	Phillip	CIMMYT
Amikuzuno	Joseph	University for Development Studies
Andresen	Jeffrey	Michigan State University
Antle	John	Oregon State University
Ashfaq	Muhammad	University of Agriculture, Faisalabad-Pakistan
Assad	Eduardo	EMBRAPA
Asseng	Senthold	University of Florida
Athanasiadis	Ioannis	Democritus University of Thrace
Baethgen	Walter	IRI/Columbia University
Baigorria	Guillermo	University of Nebraska-Lincoln
Balser	Teri	University of Florida
Banse	Martin	Thuenen-Institute
Bantilan	Cynthia	ICRISAT
Barreda	Carolina	International Potato Center
Basso	Bruno	Michigan State University
Bationo	Andre	AGRA
Beletse	Yacob	Agricultural Research Council
Bellocchi	Gianni	French National Institute for Agricultural Research (INRA)
Bernardi	Michele	FAO
Bertuzzi	Patrick	INRA - US Agroclim - Avignon
Best	Neil	University of Chicago
Blanc	Elodie	MIT
Boote	Kenneth	University of Florida
Bortolon	Elisandra	EMBRAPA- Natl Lab of Fisheries, Aquaculture and Agricultural Systems
Bortolon	Leandro	EMBRAPA - Natl Lab of Fisheries, Aquaculture and Agricultural Systems
Cammarano	Davide	University of Florida
Cane	Mark	Columbia University, IRI
Cha	SuYoung	Seoul National University
Chryssanthacopoulos	James	Columbia University
Chung	Uran	CIMMYT
Ciaian	Pavel	European Commission, Joint Research Center
Claessens	Lieven	ICRISAT
Cole	Jefferson	U.S. EPA
Condori	Bruno	International Potato Center
Confalonieri	Roberto	University of Milan
Costello	Christine	University of Missouri
Cox	Carolyn	University of Florida
Craufurd	Peter	CIMMYT
Danda	Raji Reddy	Acharya N.G.Ranga Agricultural University
Darai	Rajendra	Nepal Agricultural Research Council(NARC)
De Groot	Hugo	Alterra, Wageningen UR
de Noblet	Nathalie	CNRS / LSCE
Debats	Stephanie	Princeton University

AgMIP • 4TH ANNUAL GLOBAL WORKSHOP

LAST NAME	FIRST NAME	ORGANIZATION
Denisov	Vitalij	Klaipeda University
Deryng	Delphine	University of East Anglia
Dickson	Caleb	Oregon State University
Donatelli	Marcello	CRA
Downie	Katie	International Livestock Research Institute
Dumas	Patrice	CIRAD/CIRED
Durand	Jean-Louis	INRA
Durigon	Angelica	Center for Nuclear Energy in Agriculture - University of São Paulo
Echereobia	Christopher Ogbuji	Federal University of Technology Owerri, Nigeria
Edgerton	Mike	Monsanto Company
Elliott	Joshua	University of Chicago
Ewert	Frank	University of Bonn
Fiona	Ehrhardt	INRA-CODIR-DSENV
Fleisher	David	USDA
Frank	Stefan	IIASA
Furlow	John	USDA
Gangwar	Babooji	PDFSR
Garrett	Karen	Kansas State University
Gayler	Sebastian	WESS - Water & Earth System Science Competence Cluster
Gerik	Thomas	Texas A&M AgriLife Research
Giacomo	De Sanctis	INRA - US Agroclim - Avignon
Gilbert	Xavier	Imperial College London
Glotter	Michael	University of Chicago
Gopinath	Munisamy	Oregon State University
Grace	Peter	Queensland University of Technology
Greene	Arthur	IRI/Columbia University
Gueneau	Arthur	IFPRI
Guntuku	Dileepkumar	ICRISAT
Gustafson	Dave	ILSI Research Foundation - CIMSANS
Hansen	James	International Research Institute for Climate and Society
Hatfield	Jerry	USDA-ARS-NLAE
Hendley	Paul	Phasera Ltd
Herrero	Mario	CSIRO
Hickman	Jonathan	Columbia University
Hillel	Daniel	Columbia University
Hoffmann	Holger	Institute of Crop Science and Resource Conservation (INRES), University of Bonn
Hohenstein	William	USDA Climate Change Program Office
Holzworth	Dean	CSIRO
Hoogenboom	Gerrit	Washington State University
Howden	Mark	CSIRO
Hudson	Nick	Columbia
Hussain	Jamshad	University of Agriculture, Faisalabad-Pakistan
Ines	Amor VM	IRI/Columbia University
Islam	Shahnila	International Food Policy Research Institute (IFPRI)
Iyob	Biniam	USAID-Bureau for Food Security
Jahn	Molly	University of Wisconsin-Madison
Jain	Atul	University of Illinois
Jalandoni	Alessandra	University of the Philippines (Open University)
Janssen	Sander	Alterra
Jones	Andrew	Lawrence Berkeley Laboratory

LAST NAME	FIRST NAME	ORGANIZATION
Jones	James W	University of Florida
Jorgenson	Jason	University of Reading
Justino	Flavio	Universidade Federal de Viçosa
Kadiyala	Dakshina Murthy	ANGR Agricultural University
Kakani	Vijaya Gopal	Oklahoma State University
Kandaswamy	Mahendran	Tamil Nadu Agricultural University
Karunaratne	Asha	Sabaragamuwa University of Sri Lanka
Kersebaum	Kurt Christian	Leibniz Centre for Agricultural Landscape Research
Kihara	Job	CIAT
Kiker	Gregory	University of Florida
Kilavi	Mary	Kenya Meteorological Service
Kim	Dae-jun	Kyung Hee University
Kim	Kwang Soo	Seoul National University
Kinfe	Yosef Welderufael	Ethiopian Agricultural Transformation Agency (ATA)
King	Anthony	Oak Ridge National Laboratory
Koch	Friedrich	Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO)
Kong	Angela	NASA-GISS/Columbia University
Küchy	Martin	Thünen Institute of Market Analysis
Kuhlgatz	Christian	Thünen Institute of Market Analysis
Kyle	Page	Pacific Northwest National Laboratory
Laborde	David	IFPRI
Lee	Christine	NASA
Levy	Marc	Columbia
Li	Tao	International Rice Research Institute
Lifson	Shari	Columbia University
Liu	Bing	Nanjing Agricultural University
Liu	Leilei	Nanjing Agricultural University
Liu	Xing	Purdue University
Lotze-Campen	Hermann	Potsdam Institute for Climate Impact Research (PIK)
MacCarthy	Dilys	University of Ghana
MacGregor	Bob	Agriculture and Agri-Food Canada
Magrin	Graciela Odilia	INTA
Mamo	Girma	EIAR
Manici	Luisa Maria	CRA - Research Centre for Industrial Crops
Marin	Fabio	University of Sao Paulo
Masikati	Patricia	CGIAR
Mason-D'Croz	Daniel	International Food Policy Research Institute (IFPRI)
Masutomi	Yuji	Center for Environmental Science in Saitama
Mauzerall	Denise	Princeton University
McDermid	Sonali	Columbia University
Mearns	Linda	National Center for Atmospheric Research
Melton	Forrest	NASA
Mencos Contreras	Erik Alejandro	Columbia University
Meza	Francisco	Centro de Cambio Global Pontificia Universidad Catolica de Chile
Mitter	Hermine Christiane	University of Natural Resources and Life Sciences Vienna, Austria
Monier	Erwan	MIT
Moscuzza	Alessandro	UKAID-DFID
Mu	Jianhong	Oregon State University
Müller	Christoph	Potsdam Institute for Climate Impact Research
Muñoz-Carpena	Rafael	University of Florida
Musumba	Mark	Columbia University

LAST NAME	FIRST NAME	ORGANIZATION
Mutter	Carolyn	Columbia University
Nazareth	Vijay	University of Florida
Nedumaran	Swamikannu	ICRISAT
Negm	Lamyaa	NCSU
Nelson	Gerald	University of Illinois at Urbana-Champaign
Nendel	Claas	Leibniz Centre for Agricultural Landscape Research (ZALF)
Ngugi	Moffatt	USAID
Niemeyer	Stefan	European Commission, Joint Research Centre
Nissanka	Sarath	University of Peradeniya
OLeary	Garry	Department of Environment and Primary Industries
Olesen	Jørgen E.	Aarhus University
Olin	Stefan	Lund University
Parry	Martin	Imperial College
Pinto	Hilton	State University of Campinas - Unicamp
Ponnusamy	Paramasivam	TNAU
Porter	Cheryl	University of Florida
Prescott	Ryan	Agriculture and Agri-Food Canada
Pugh	Thomas	Karlsruhe Institute of Technology / IMK-IFU
Qian	Budong	Agriculture and Agri-Food Canada
Ramarohetra	Johanna	IRD
Rao	KPC	ICRISAT-Nairobi
Ren	Xiaolin	National Center for Atmospheric Research
Reynolds	Matthew	CIMMYT
Ripoche-Wachter	Dominique	INRA - US Agroclim - Avignon France
Rising	James	Columbia
Rivera	Vilma	The Earth Institute
Robinson	Sherman	International Food Policy Research Institute (IFPRI)
Rodriguez	Gabriel	Instituto Nacional de Tecnologia Agropecuaria - INTA
Rooyen	Andre	ICRISAT
Rosegrant	Mark	IFPRI
Rosenzweig	Cynthia	NASA-GISS/Columbia University
Rötter	Reimund	MTT Agrifood Research Finland
Ruane	Alex	NASA GISS
Sachs	Jeffrey	Columbia University
Sands	Ron	USDA-Economic Research Service
Schneider	Kate	Bill & Melinda Gates Foundation
Schoenhart	Martin	University of Natural Resources and Life Sciences
Seifert	Christopher	Stanford University
Semenov	Mikhail	Rothamsted Research
Shelia	Vakhtang	Washington State University
Sinabell	Franz	Austrian Institute of Economic Research
Singh	Balwinder	CIMMYT
Sivakumar	Mannava V.K.	WMO
Skalsky	Rastislav	International Institute for Applied Systems Analysis
Snow	Val	AgResearch
Soussana	Jean-Francois	INRA, France
Springer	Nathaniel	Agriculture Sustainability Institute, UC Davis
Springmann	Marco	University of Oldenburg
Stockle	Claudio	Washington State University
Subash	Nataraja	PDFSR

LAST NAME	FIRST NAME	ORGANIZATION
Sullivan	Clare	Columbia University
Sultan	Benjamin	IRD-LOCEAN
Sun	Liqiang	North Carolina State University
Tao	Fulu	MTT
Tedeschi	Luis	Texas A&M University
Tenywa	Moses	Makerere University Agricultural Research Institute, Kabanyolo (MUARIK)
Thibodeau	Andrew	Columbia University
Thorburn	Peter	CSIRO
Thornton	Philip	ILRI, CCAFS
Tiscornia	Guadalupe	INIA Uruguay
Tollenaar	Matthijs	Monsanto Co.
Tommaso	Stella	University of Milan
Topaj	Alex	Agrophysical Research institute
Travasso	María Isabel	INTA
Valdivia	Roberto	Oregon State University
van der Mensbrugghe	Dominique	FAO
Van Doren	Saratha	Monsanto Co
van Ittersum	Martin	Wageningen University
van Meijl	Hans	LEI, Wageningen UR
Vanuytrecht	Eline	KU Leuven
Vellingiri	Geethalakshmi	Tamil Nadu Agricultural University
Villalobos	Christopher	University of Floirda
von Lampe	Martin	Organisation for Economic Co-operation and Development OECD
Waha	Katharina	Potsdam Institute for Climate Impact Research
Wajid	Syed Aftab	University of Agriculture, Faisalabad-Pakistan
Wall	Gerard W	USDA-ARS
Wallach	Daniel	INRA
Wang	Enli	CSIRO Land and Water
Wei	Xiong	IIASA
Weinberg	Marca	USDA-ERS
Whitbread	Anthony	University of Goettingen, Germany
Wiebe	Keith	IFPRI
Wieruszeski	Sophie	CNRS - LSCE
Willenbockel	Dirk	Institute of Development Studies at the University of Sussex
Wilson	Lloyd	Texas A&M AgriLife Research - Beaumont/Eagle Lake
Winchester	Niven	MIT
Winter	Jonathan	Dartmouth College
Wood	Stan	Bill and Melinda Gates Foundation
Wouk	Byron	Columbia
Xia	Lili	Rutgers University
Yan	Nana	Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences
Yao	Xia	Nanjing Agricultural University
Youssef	Mohamed	NCSU
Zeng	Hongwei	The Institute of Remote Sensing and Digital Earth (RADI), Chinese Academy of Sciences (CAS)
Zhang	Meng	University of Florida
Zhang	xin	Princeton University
Zhu	Yan	Nanjing Agricultural University
Zubair	Lareef	Foundation for Environment, Climate, and Technology, Sri Lanka

VOLUNTEERS

Toyah Barigye
Onella Cooray
Dannie Dinh
Vivianne Reynoso
Bo Yeon Jang
Ece Ersoz
Salama Shelton
Daniel Nothaft
Shifali Gupta
Chenyan Lu
Monica Pasqulino
Molly Schneider
Molly Slotznick
Harneet Kaur
Yun Lu
Colin Gannon
Lea Cohen

ACKNOWLEDGEMENTS

AgMIP would like to thank the Earth Institute/Columbia University for hosting the Global Workshop and providing meeting support, especially Vilma Gallagher and her team for assisting with meeting logistics. We would also like to thank the team at the Columbia Faculty House for their dedication and attention to detail.

AgMIP would also like to thank all those that contributed time and effort to making this workshop a success.

LINKS TO ONLINE MATERIAL

Agenda:
http://www.agmip.org/wp-content/uploads/2013/12/4th-AgMIP-GW-Agenda-final1.pdf

Participant List:
http://www.agmip.org/wp-content/uploads/2013/12/Participant-Listing-10.24.pdf

Presentations:
http://www.agmip.org/4th-annual-global-workshop-presentations/

Work Group Reports:
http://www.agmip.org/4th-annual-global-workshop-work-group-reports/

PDFs of Posters:
http://www.agmip.org/4th-annual-global-workshop-posters/

Poster Abstracts:
http://www.agmip.org/wp-content/uploads/2013/12/4th-Annual-GW-Poster-Program-Final1.pdf

Appendix A: Poster Titles and Abstracts

Assessing Climatic Risk in Rice Productivity Using Integrated Climate, Crop and Economic Modeling Techniques

A. Ahmad et al.
Poster position: A2

A. Ahmad, M. Ashfaq, A. Wajid, G. Rasul, T. Khaliq, S. Ahmad, W. Naseem, J. Hussain, M.H. Rahman, U. Saeed, S.A.A. Naqvi and G. Hoogenboom

Rice-wheat cropping zone of Pakistan is facing accelerated incidence rate of extreme weather events. AgMIP-Pakistan is working to quantify the climate change effects on rice crop currently at farm levels using climate, crop and economic models. Five rice producing districts were surveyed and data of 155 farmers were collected for crop and economic models. DSSAT and APSIM were used for crop simulations under present and future climate scenarios. The yield simulations of crop models were obtained separately for baseline (1981-2010) and five future scenarios using 5 GCMs with RCPs 8.5 between 2040 and 2069. The predicted mean data of GCMs showed about 2°C temperature and 0.13% increase in rainfall till mid-century (2040-2069). The performance of DSSAT was relatively better than APSIM with RMSE (425.46, 440.48 kg ha^{-1}), d-stat (0.784, 0.786) and R^2 (0.52, 0.44), respectively. Models showed a decreasing trend in yield by 30, 20, 13, 7 and 6% (mean 15.2%) in DSSAT and 19, 14, 16, 15 and 18% (mean 17.2%) in APSIM, using five GCMs GFDL, MPI-ESM, CCSM4, MICROS and Had-GEM, respectively. The overall results of TOA-MD model without adaptation showed about 26 and 25 percent gainers for DSSAT and APSIM models, respectively. The results of analysis with adaptation showed that the numbers of adopters would be 64 and 42 percent in APSIM and DSSAT, respectively. Mean net returns per farm were calculated as $2511 and $3728 for without and with-adaptation scenarios for overall APSIM model. Similarly, the mean net returns per farm were calculated as $2505 and $2671 for without and with-adaptation scenarios in case of DSSAT model.

Representative Agricultural Pathways and Climate Impact Assessment for Pacific Northwest Agricultural Systems

John Antle et al.
Poster position: B1

John Antle[1], Elina Mu[2], Hongliang Zhang[3], Susan Capalbo[4], Sanford Eigenbrode[5], Chad Kruger[6], Claudio Stockle[7], J.D. Wolfhorst[8]
[1] Professor of Agricultural and Resource Economics, Oregon State University
[2] Post-doctoral researcher, Agricultural and Resource Economics, Oregon State University
[3] Graduate research assistant, Oregon State University
[4] Professor and Department Head, Agricultural and Resource Economics, Oregon State University
[5] Professor of Entomology and REACCH Project Director, University of Idaho
[6] Director, Center for Sustaining Agriculture and Natural Resources, Washington State University
[7] Professor and Chair, Department of Biological Systems Engineering, Washington State University
[8] Professor, Social Sciences Research Unit, University of Idaho

Representative Agricultural Pathways (RAPs) are projections of plausible future biophysical and socio-economic conditions used to carry out climate impact assessments for agriculture. The development of RAPs is motivated by the fact that the various global and regional models used for agricultural climate change impact assessment have been implemented with individualized scenarios using various data and model structures, often without transparent documentation or public availability. These practices have hampered attempts at model inter-comparison, improvement, and synthesis of model results across. This poster aims to (1) present RAPs developed for the principal wheat-producing region of the Pacific Northwest, and to (2) combine these RAPs with downscaled climate data, crop model simulations and economic model simulations to assess climate change impacts on winter wheat production and farm income. This research was carried out as part of a project funded by the USDA known as the

Regional Approaches to Climate Change in the Pacific Northwest (REACCH).

To develop RAPS for the REACCH region, project scientists and other experts with knowledge of the region's agricultural systems are working together through a step-wise process designed to record and document the information used to create RAPS. The REACCH team developed 3 RAPS to represent the future agricultural pathways and scenarios, labeled Business-as-Usual, Dysfunctional World and Aggressive Climate Policy. In each RAP, key variables are identified, narratives are constructed, and quantitative values are assigned. These RAPS are then used by the modeling team to simulate climate change impacts and how technological innovations will help farmers adapt to changing environmental and economic conditions.

TOA-MD: A New Approach to Assess Climate Change Impacts and Adaptation for Agricultural Households

John Antle et al.
Poster position: C1

John M. Antle[1], Roberto O. Valdivia[1*]
[1] Department of Agricultural and Resource Economics, Oregon State University
* Corresponding:
Roberto.Valdivia@oregonstate.edu

Despite the growing attention paid to the potential for climate change to affect climate variability and extremes, most models being used to assess climate change impacts on agricultural producers are based on averaged or aggregated data over relatively large populations. The only sense in which such studies can assess vulnerability – defined as the risk of a negative impact – is in terms of average impacts on groups of farm households stratified by some criterion such as a spatial unit, typically a political unit or an agro-ecozone. In this presentation we present a new economic simulation approach that combines available historical data, statistical models, down-scaled climate data, experimental data and process-based production models, to approximate future distributions of production and associated economic outcomes such as farm net returns. We also show how this model can be used to parameterize an economic impact assessment model, the Tradeoff Analysis Model for Multi-Dimensional Impact Assessment (TOA-MD; Antle 2011; Antle and Valdivia 2011). TOA-MD provides the capability to go beyond the analysis of averaged or aggregated data, by representing the distributions of economic, environmental and social outcomes in heterogeneous populations of farm households. When used for climate impact assessment, the TOA-MD model can be used to show how the distributions of outcomes are affected by climate and by adaptations farmers may undertake in response to climate change.

TOA-MD: A Novel Simulation Approach to Multi-Dimensional Impact Assessment

John Antle et al.
Poster position: C2

John M. Antle[1], Roberto O. Valdivia[1*]
[1] Department of Agricultural and Resource Economics, Oregon State University
* Corresponding:
Roberto.Valdivia@oregonstate.edu

This poster presents a novel approach to impact assessment of agricultural systems which has been implemented as the TOA-MD simulation model. The TOA-MD Model is a unique simulation tool for multi-dimensional impact assessment that uses a statistical description of a heterogeneous farm population to simulate the adoption and impacts of a new technology, a change in environmental conditions, and ecosystem services supply. TOA-MD is a parsimonious approach to impact assessment that is particularly well-suited to ex ante assessment. Unlike conventional ex post statistical or econometric methods that require large, detailed cross-sectional or panel data sets, TOA-MD is designed for ex ante assessment and can be implemented with various types of data, including survey, experimental, and modeled data, together with technological and socio-economic scenarios derived from experts and stakeholders. The poster provides an overview of the approach

and the TOA-MD model software, and illustrates the use of the model with results from an application of the model to assess impacts of the adoption of Integrated Agriculture-Aquaculture in Malawi.

Representative Agricultural Pathways and Scenarios: A Trans-Disciplinary Approach to Agricultural Model Inter-comparison, Improvement and Climate Impact Assessment

John Antle et al.
Poster position: C16

John Antle[1], Roberto Valdivia[1*], Lieven Claessens[2], Gerald Nelson[3], Cynthia Rosenzweig[4], Alex Ruane[4], and Joost Vervoort[5]
[1] Oregon State University
[2] International Crops Research Institute for the Semi-Arid Tropics, ICRISAT
[3] International Food Policy Research Institute, IFPRI
[4] NASA Goddard Institute for Space Studies
[5] University of Oxford/CCAFS
[*] Corresponding:
Roberto.Valdivia@oregonstate.edu

This poster presents concepts and methods for the development of global and regional Representative Agricultural Pathways and Scenarios that can be used for agricultural model inter-comparison, improvement and impact assessment. These pathways and scenarios are based on the integrated assessment framework developed by the Agricultural Model Inter-comparison and Improvement Project. This framework shows that both bio-physical and socio-economic drivers are essential components of agricultural pathways and logically precede the definition of adaptation and mitigation scenarios that embody associated capabilities and challenges. Based on this approach, we describe a trans-disciplinary process to design pathways and then to translate pathways into scenarios for both bio-physical and economic models that are components of agricultural integrated assessments of climate impact, adaptation and mitigation. To implement this trans-disciplinary approach, we propose a step-wise process similar to the "story and simulation" (SAS) approach to scenario design that brings together expertise from the relevant disciplines to design pathways, and then use these pathways to design consistent scenarios (i.e., model-specific parameters) for crop and livestock simulation models and economic impact assessment models. We present an example of modeling impacts of climate change using the RAPs concept.

Improving Global Agricultural Production by Mitigating Ozone Damages to Crops via Methane Emission Controls and Ozone Resistant Cultivar Selection

Shiri Avnery et al.
Poster position: A4

Shiri Avnery, Denise L. Mauzerall, Arlene M. Fiore

No abstract provided.

Global Crop Yield Reductions due to Surface Ozone Exposure: Crop Production Losses and Economic Damage in 2000 and 2030 under Two Future Scenarios of Ozone Pollution

Shiri Avnery et al.
Poster position: A3

Shiri Avnery, Denise L. Mauzerall, Junfeng Liu, and Larry W. Horowitz

No abstract provided.

Using EPIC for simulating global wheat production: model set-up and future projections

Juraj Balkovič et al.
Poster position: D2

Juraj Balkovič[1], Marijn van der Velde[1], Rastislav Skalský[1], Wei Xiong[1], Nikolay Khabarov[1], Alexey Smirnov[1], Michael Obersteiner[1]
[1] International Institute for Applied Systems Analysis (IIASA), Ecosystem Services and Management Program, Schlossplatz 1, A-2361 Laxenburg, Austria

With a current production of ~700 Mt, wheat is the third largest crop globally, and an essential source of calories in human diets. Sustainable intensification of wheat systems to satisfy rising food demands and the impacts of future climate on wheat yields are widely discussed aspects of securing and sustaining future world wheat production. In this study we present a global EPIC implementation to quantify global wheat production under new generation of climate change scenario. The global modelling system was constructed at 5 arc-min grid by combining the EPIC, v. 0810 model and GIS layers on soils, relief, administrative units, 0.5 arc-deg weather grid, wheat growing periods and fertilizers consumption around 2000 (Mueller et al. 2012). The Princeton weather data were used for the baseline time period (1990 - 2000) and bias-corrected HadGEM2-ES GCM simulations for RCP2.6, 4.5, 6.0 and 8.5 concentration scenarios for the future projections (2041 – 2060, 2081 – 2100). The EPIC model performed satisfactorily in the prediction of average historical wheat yields and production. EPIC simulations with four climate change projections revealed spatially heterogeneous impacts on actually achieved and potential wheat yields across regions and RCP scenarios. From the global perspective and averaged for all RCPs, global wheat production on currently cultivated cropland would likely decrease respectively by 7 and 12% in the 2050s and 2090s because of worsening climatic conditions. There are many differences among regions pointing to spatially differing effects of the climatic drivers on wheat growth.

Impacts of projected climate change scenarios on the production and prices of staple and nutritionally important crops in the Southern Africa: project overview

Y. Beletse et al.
Poster position: B5

Y. Beletse[1], W.Durand[2], O.Crespo[3], C.Nhemachena[6], W.Tesfuhuney[5], M Jones[4], M.Teweldemedhin[7], M.Gamedze[5], P. Gwimbi, T. Mpusaing, PM Bonolo[7], J Siyanda[6] and D Cammarano[8]
[1] Agricultural Research Council-Roodeplaat, KuwaMahlanga road, Pretoria 0001, South Africa
[2] Agricultural Research Council-Small Grain Institute, Potchefstroom, South Africa
[3] Climate System Analysis Group, Environmental and Geographical Science Department, University of Cape Town, 7701 Rondebosch, South Africa
[4] South African Sugarcane Research Institute, 170 Flanders Drive. Mount Edgecombe. KwaZulu-Natal
[5] University of the Free State, PO Box 339 (int 60) Bloemfontein 9300 South Africa
[6] Human Sciences Research Council, Pretorius street, 134 Pretoria, South Africa
[7] Polytechnic of Namibia, Storch Street
[8] Agricultural & Biological Engineering Department, University of Florida, Gainesville, FL 32611, USA

SAAMIP is a regional AgMIP project with members from South Africa, Lesotho, Swaziland, Botswana and Namibia. The objective of the project is to assess, using climate, crop and economic models, the impacts of projected climate change on agricultural production and socio economics factors in southern Africa. Two crop models (DSSAT and APSIM) were calibrated against detailed field data collected at 'sentinel sites' in each of the countries. Climate dataset for baseline (historical, 1980-2010) and future (2040-2070) was then used by the two crop models to generate a yield change between baseline and future. This information, along with socio economic data and farming communities cropping regions are used as input in the TOA-MD economic model to assess climate change

adaptation strategies and their physical and social impacts on farming communities.

The data were gathered from five countries in collaboration with 10 institutions in Southern Africa. The frequent training and the workshops helped the team to clarify the methodologies for using the inputs and for making assumptions for running the climate, crop, and economic models. In addition, the team achieved a better understanding of Regional Agricultural Pathways (RAPs), and the process of developing RAPs for using them in the economic model. Southern Africa is predicted to be affected by increase in temperature and variable rainfall. Without sufficient adaptation measures, the region will likely to suffer negative impacts on several crops that are important in securing food in the region.

Integrated assessment of impacts of projected climate change on maize production in the Bethlehem District, Free State, South Africa

Y. Beletse et al.
Poster position: B6

Y. Beletse[1], W.Durand[2], C.Nhemachena[6], O.Crespo[3], W.Tesfuhuney[5], M Jones[4], M.Teweldemedhin[7], M.Gamedze[5], PM Bonolo[7], and J Siyanda[6]
[1] Agricultural Research Council-Roodeplaat, KuwaMahlanga road, Pretoria 0001, South Africa
[2] Agricultural Research Council-Small Grain Institute, Potchefstroom, South Africa
[3] Climate System Analysis Group, Environmental and Geographical Science Department, University of Cape Town, 7701 Rondebosch, South Africa
[4] South African Sugarcane Research Institute, 170 Flanders Drive. Mount Edgecombe. KwaZulu-Natal
[5] University of the Free State, PO Box 339 (int 60) Bloemfontein 9300 South Africa
[6] Human Sciences Research Council, Pretorius street, 134 Pretoria, South Africa
[7] Polytechnic of Namibia, Storch Street

The impacts of projected climate change on maize production were assessed for 400 maize fields in the Bethlehem District, in the Free State Province, South Africa using climate, crop and economic models. Data used as input by crop and economic models were field crop boundaries, satellite imagery classification, yield surveys, land type classification. Two crop models (DSSAT and APSIM) were calibrated for the local condition using observed climate, soil and agronomic data in the region. Past (1980-2010) and future (5 GCMs for the time period 2040-2070, with RCP8.5 and CO_2 of 571ppm) maize production was simulated and the yield change between future and baseline was determined. The simulated yield changes were used as input into the Trade of Analysis for multi-dimensional impact assessment model (TOA-MD) to characterize the economic impact of climate change. Projections of future changes in climate for South Africa showed an increase in temperature and variability in rainfall, increasing the risk of crop failure and food insecurity in the region. Overall, DSSAT and APSIM simulated a decrease of maize production using projected changes in climate in the region, which will have major implication to food security. The TOA-MD projections showed that about 74% of the farmers in the district would benefit from climate change.

MODEXTREME - MODelling vegetation response to EXTREMe Events

Gianni Bellocchi et al.
Poster position: D12

Gianni Bellocchi[1], Francisco Villalobos[2], Marcello Donatelli[3], Ole B. Christensen[4], Pasquale Steduto[5], Roberto Confalonieri[6], Ioannis N. Athanasiadis[7], Irina Carpusca[8], Claudio Stöckle[9]
[1] Institut National de la Recherche Agronomique (INRA), Clermont-Ferrand, France
[2] Universidad de Córdoba (UCO), Córdoba, Spain
[3] CRA-CIN, Consiglio per la Ricerca e la sperimentazione in Agricoltura, Bologna, Italy
[4] Danmarks Meteorologiske Institut, Copenhagen, Denmark

[5] Food and Agriculture Organization of the United Nations (FAO), Rome, Italy
[6] Università degli Studi di Milano, Milan, Italy
[7] Democritus University of Thrace, Xanthi, Greece
[8] INRA-Transfert, Paris, France
[9] Washington State University, Pullman, United States of America

Extreme weather events are combinations of environmental drivers occurring with a low frequency and negatively impacting on agricultural productions. The project EU-FP7 MODEXTREME (coordination: INRA; grant: 2,000,000 €; start: November 1st, 2013; duration: three years) has the overarching goal to improve the capability of biophysical crop and grassland models by integrating climatic variability and extreme events (mainly high/low temperatures; water deficit/excess). The project includes 18 worldwide partners (seven universities, eight research institutions, one international organization, one software enterprise and one service management society). Generically reusable software units implementing libraries of process models will be created to extend existing modelling capabilities to extreme weather impacts. Estimates from existing and new modelling solutions will be both compared on a variety of datasets and evaluated with respect to medium-term trajectories of future climate. This will be achieved via the multi-model platform for plant growth and development simulations BioMA (The Biophysical Model Application) and will support short- and medium-term forecasts in Europe via the Monitoring Agricultural ResourceS (MARS) workflow of European Commission Joint Research Centre. Project results will also contribute to improve food security monitoring and early warning systems outside Europe (Argentina, Brazil, China, South Africa, United States) via transfer of knowledge to local stakeholders.

Sentinel Site Data for Model Improvement and Application – Definitions and Characterization

K. J. Boote et al.
Poster position: C3

K. J. Boote[1], C. H. Porter[2], J. W. Jones[2], P. J. Thorburn[3], and G. Hoogenboom[4]
[1] Agronomy Dept., University of Florida, Gainesville, FL 32611
[2] Agric and Biol. Engr. Dept., University of Florida, Gainesville, FL 32611
[3] CSIRO, Brisbane, Australia
[2] Washington State University, Prosser, WA

Quality experimental data are a necessary pre-requisite for use by crop modelers in order to calibrate, evaluate, and improve models for ability to respond to climatic change factors of carbon dioxide, temperature, precipitation and the interaction with management and genetic factors. Here we describe criteria for characterizing the quality, quantity, reliability/accuracy, and value of measured crop, soil, weather, and management data for modeling purposes. AgMIP is establishing a data base for storage of crop, soils, and weather data to be used for running and testing of models. The data sets are categorized as platinum, gold, silver, or copper based on quality. Platinum indicates highest quality observed data for model evaluation, and improvement, with a full complement of variables including in-season and end-of-season crop growth and yield measurements, with observed site-specific data on soil, weather, and management conditions for model inputs. The second-tier 'gold sentinel' sites have sufficient information for model calibration and evaluation, but lack the breadth of variables or intensity of data available, and weather or soil data may not be measured on-site. The third-tier 'silver sentinel sites' is characteristic of yield trials that plant breeders manage, where end-of-season yield is measured, along with management inputs of planting date, irrigation, and fertilization. However, in-season measurements and phenology are lacking, and weather and soil data are not site-specific. Copper sentinel sites have fair quality data such as site-specific farm survey yields or variety trial yields, but local

weather and soil information are not available and some management data are approximated.

Need Across-Models-Across-Crops Testing of Evapotranspiration and Crop Water Use Against Data

K. J. Boote et al.
Poster position: C4

K. J. Boote[1], Co-Coordinator, AgMIP Crop Modeling, assisted by AgMIP-Maize, AgMIP-Wheat, and Global Gridded Modelers
[1] Dept of Agronomy, University of Florida, Gainesville, FL 32611

All crop models, whether site-specific or global-gridded and regardless of crop, simulate daily crop transpiration and soil evaporation during the crop life cycle, resulting in seasonal crop water use. Modelers use several methods for predicting daily potential evapotranspiration (ET), including FAO-56, Penman-Monteith, Priestley-Taylor, Hargreaves, full energy balance, and transpiration water efficiency. They use extinction equations to partition energy to soil evaporation or transpiration, depending on leaf area index. Most models simulate soil water balance and soil-root water supply for transpiration, and limit transpiration if water uptake is insufficient, and thereafter reduce dry matter production. Intercomparisons of multiple crop and global gridded models in AgMIP show surprisingly large differences in simulated ET and crop water use for the same climatic conditions. Unfortunately, model intercomparison alone is not enough to know which models are correct. There is an urgent need to test these models against field-observed data on ET and seasonal crop water use. Because water resources are so important for production, it is crucial that we establish a new effort across all crops and across models, with the goal of testing and improving the models for predicting ET and crop water use. Two types of data include: 1) season-long water use computed from soil-water balance where runoff and deep percolation are known or zero, 2) instantaneous transpiration-soil evaporation measured by lysimeters, Bowen ratio, and eddy flux systems. Special emphasis should be placed on using available FACE data to test simulated reduction in transpiration with rising CO_2.

A library of software components for plant airborne diseases simulation

S. Bregaglio et al.
Poster position: A13

S. Bregaglio[1], M. Donatelli[2], R. Confalonieri[1]
[1] Dep. of Agricultural and Environmental Sciences - Production, Landscape, Agroenergy, University of Milan, Milan, Italy
[2] CRA-CIN, Consiglio per la Ricerca e sperimentazione in Agricoltura, Bologna, Italy

The importance of including the impacts of plant diseases in crop production simulation studies is widely recognized, although an explicit coupling of disease forecasting models with crop growth models is still not operational. The increasing adoption of component-oriented programming in agro-ecological modelling could lead to fill this gap, thanks to the handling of the high complexity of the simulated biophysical processes. This work presents four independent software components aimed at simulating a generic polycyclic fungal epidemic, which can be extended with alternate approaches and reused under diverse modelling platforms. These components provide options for simulating the initial conditions of an epidemic, the progress of the disease over time driven by meteorological variables, the yield losses due to the pathogen impact and the agro management practices to reduce disease development. This platform was parameterized for wheat brown rust and rice blast disease and coupled to two crop simulators (WOFOST and WARM). These modelling solutions were evaluated via a spatially distributed sensitivity analysis exercise to gain an in-depth knowledge about model functioning and to obtain information about possible reduction or simplifications. The results indicated that the modelling solutions were sensitive to diverse parameters according to the pathogen simulated and coherent about the small relevance of parameters belonging to same processes in the two pathosystem tested. The framework presented

here represents one step to move beyond both statistical models and a misuse of process based model via calibration which leads only to data fitting, instead of forecasting models.

Adaptation of a generic fungal plant disease simulator to assess blast disease (Magnaporthe oryzae Cav.) impact on rice grown in temperate conditions

S. Bregaglio et al.
Poster position: A14

S. Bregaglio[1], P. Titone[2], G. Cappelli[1], L. Paleari[1], L. Tamborini[2], M. Donatelli[3], R. Confalonieri[1]
[1] Dep. of Agricultural and Environmental Sciences - Production, Landscape, Agroenergy, University of Milan, Milan, Italy
[2] CRA-SCS, Consiglio per la Ricerca e sperimentazione in Agricoltura, Lodi, Italy
[3] CRA-CIN, Consiglio per la Ricerca e sperimentazione in Agricoltura, Bologna, Italy

The blast disease (Magnaporthe oryzae) is the primary constraint of rice production worldwide and it is present in more than 85 countries, causing severe epidemics especially in paddy rice grown in temperate regions. Yield losses are around 10-30% of the total world production. Since years researchers started developing models to forecast the evolution of blast epidemics and to support farmers in the scheduling of fungicide sprays. Most of the available models were evaluated in Asian rice growing areas and only in few cases they were coupled with rice simulators to consider blast impact on leaf area and biomass accumulation, to obtain the quantification of yield losses. This work presents the adaptation of a generic platform for the simulation of blast epidemics and its coupling with a rice crop model. The modelling solution was run in Italian rice cultivated areas (first European producer) by considering multiple years and cultivars. The number of disease assessments was 274, organized in a scale ranging from 0 to 5. Results showed good performances both in calibration and evaluation datasets (R^2=0.813 and 0.783, respectively), clearly indicating its suitability in responding to the heterogeneity of the agro-meteorological conditions explored. When converted to ordinal values, the simulated blast impacts matched visual assessments in 50.3% of cases, and in 37.6% they missed reference values by one rank. Given the massive datasets used for its evaluation, this modelling solution will be applied in climate change scenarios to assess the potential future impact of blast disease on European rice productions.

Biophysical and economic constraints on agricultural intensification in global diet scenarios

Thierry Brunelle et al.
Poster position: A9

Thierry Brunelle, François Souty, Patrice Dumas and Bruno Dorin

Globalization drives a process of diet convergence, and in so doing increases the uncertainty about future patterns of food consumption. To address this issue we map the range of possible future diet changes and explore their impact on agriculture using the Nexus Land Use model. Four scenarios built on distinct assumption on the diet convergence process depict very contrasting visions on agricultural systems in 2050. The study focuses on agricultural intensification, taking into account economic and biophysical constraints. A non-linear response of fertilizer on cropland and a potential yield limit allows to represent decreasing returns of fertilizer application at high yields. Land-use change is driven by a trade-off between the extensive system with grazing ruminants, established on the lands with lowest fertility, and the intensive system with mixed livestock and cropland. To assess the accuracy of model results, the model ability to reproduce past observations is evaluated through a backcasting exercise.

Simulation of climate change impacts on rice yield and pre-harvest quality in Latin America

G. Cappelli et al.
Poster position: C14

G. Cappelli[1], S. Bregaglio[1], M. Donatelli[2], R. Confalonieri[1]
[1] Dep. of Agricultural and Environmental Sciences - Production, Landscape, Agroenergy, University of Milan, Milan, Italy
[2] CRA-CIN, Consiglio per la Ricerca e sperimentazione in Agricoltura, Bologna, Italy
[3] University of East Anglia

Despite the large availability of models simulating crop growth and development, few operational approaches have been developed to assess pre-harvest quality of agricultural productions. This represents a clear gap of knowledge researchers are trying to fill, in light of the evidences of a climate change-driven decline in nutritional properties of important food crops, with direct implications on the economic value of productions and on food security issues. This contribution presents an assessment of pre-harvest rice quality under different climate change scenarios in Latin America. Simulations were performed using the BioMA platform, in which the WARM rice model was linked to modelling approaches simulating grain amylose and protein contents, and the occurrence of chalkiness and fissured grains. Simulations were performed at 25x25 km spatial resolution for all the Latin American rice districts and results were aggregated at national level. Despite some differences due to emission scenarios and general circulation models, simulations revealed an overall maintenance of current production levels, whereas a general decay of quality variables is expected, especially in countries where severe climatic anomalies are foreseen (Brazil and Mexico). The negative impact on quality will be more relevant for Japonica cultivars compared to Indica ones, coherently with the different thermal requirements for starch synthesis for the two ecotypes. Our projections also indicate that climate change will lead to positive effects in countries where rice will explore conditions of better adaptation, like in Chile. This analysis demonstrated the usefulness of approaches to simulate quality variables and their potential for defining effective adaptation strategies to alleviate the expected decline in rice quality.

The Extraction of Double-Cropping Areas in North Korea using Fourier Transform Analysis of Time-series MODIS Imagery

Su-Young Cha et al.
Poster position: D9

Su-Young Cha[1], Chong-Hwa Park[2], Yeo-Chang Youn[3]
[1] Research Institute for Agriculture and Life Sciences, Seoul National University
[2] Graduate School of Environmental Studies, Seoul National University
[3] Department of Forest Sciences, Seoul National University

Human-induced forest alterations in North Korea have been expanded by the severe food crisis. Many forests have been converted into cropping area. It is important to know such deforested area in North Korea, which is not easy to access by direct field survey. Here we developed a method to get the deforested area. The double cropping area, where the NDVI (Normalized Difference Vegetation Index) has double maxima in a year is the evidence of the human farming. Such double cropping area has been detected through the Fourier analysis of the time-series MODIS (Moderate Resolution Imaging Spectroradiometer) data from 2000 to 2009. The intensity of the second harmonics, i.e., the bimodal NDVI component is directly related to the double cropping areas. Crop information of South Korea was used to access the accuracy of the result. We did not find the double cropping area only in the western field area but also on the mountainous area. The Daehongdangun region known as a large collective farm in North Korea showed strong second harmonics. The methodology used in this study is useful for detecting the deforested area that is used for the double cropping in North Korea.

AgMIP Potato Pilot: A summary of progress made

Bruno Condori et al.
Poster position: C7

Bruno Condori, Carolina Barreda, David Fleischer and Roberto Quiroz

The potato crop (Solanum sp.) has a substantial social and economic importance for many developing and developed countries. This crop is dispersed around the world, growing in very high contrasting environments: from 0 to 4000 meters above sea level, latitudes from 65° to -40°, and photoperiods ranging from 12 to 15 hours. The potato cropping systems are quite variable spanning from rain-fed low input conditions to high-tech precision agriculture. A striking difference with other crops of global importance is the variation in the cultivated ploidy (2x=24, 3x=36, 4x=48 and 5x=60), conferring the crop a wide adaptation range and thus adding complexity to the assessment of the response to climate variability and change. The AgMIP potato is a new pilot of the international effort that links the climate, crop, and economic modeling communities with cutting-edge information technology to produce improved crop and economic models and the next generation of climate impact projections for the agricultural sector. So far, 28 researchers and 10 potato modeling groups have agreed to become part of this initiative. Furthermore, five sentinel sites have been selected in Bolivia, Peru, Burundi, Denmark and USA. A preliminary analysis of the yield statistics around sentinel sites - 10 to 100 tons of fresh tubers per hectare – summarizes the challenges that the trans-disciplinary team will face.

ORACLE: Opportunities and Risks of Agrosystems & forests in response to CLimate, socio-economic and policy changEs in France

Nathalie de Noblet-Ducoudré et al.
Poster position: B4

Nathalie de Noblet-Ducoudré, Iñaki Garcia de Cortazar Atauri, Julie Caubel, Anne-Isabelle Graux, Sophie Wieruszeski, Dominique Carrer, Jean-Christophe Calvet, Nabil Laania

ORACLE aims at providing spatially-gridded assessments of potential future changes in a) the functioning of agro-ecosystems, b) land uses in France at rather high resolution (8 x 8 km2). These assessments involve the production of tools and data to study the relationships between climate change and possible changes in land use, together with the impacts of changing policies. We will focus our analysis and modeling on the main components of the non-urban land use, namely crops, grasslands and forests. We will study their production as well as their environmental functionalities (GHG emission, hydrology, soil carbon storage) and develop a small set of relevant indicators. Climate-induced changes in those indicators will be analyzed and, wherever possible, their upper and lower limits will be defined. This will allow us to assess, per grid-cell, risks of dis-functioning of specific systems, potential disappearance of present-day land-uses, and potentialities of appearance of new ones. We will also try to combine the indicators with water availability to identify potential future hot-spots in France and Europe, i.e., grid-cells or regions that may experience drastic land-use changes.

Insights on land-use change will be obtained following two parallel methodologies. First, we will use the climatically-induced variations of the above-mentioned indicators to explore reshaping of farming systems, optimizing opportunities and minimizing constraints, without accounting for changes in socio-economic drivers. The propositions will rely on a) meta-analysis of published data on agronomic performances and environmental impacts of cultivation systems, and b) expert knowledge.

In the second methodology, we will jointly evaluate the impacts of changes in climatic and socio-economic drivers on anthropogenic land-uses. We will rank those impacts and identify areas where the impacts of climate change on land-uses may overrule those resulting from socio-economic changes. We will also attempt to estimate land-use change between agriculture and forest when both climatic and economic drivers change.

Results will be obtained i) at two spatial scales, namely France and hydrological basin (Seine and Leyre basins), ii) for two time horizons (2020-2050 and 2070-2100) in reference to the 1970-2000 period. Both prospective uncertainty (socio-economic scenarios, crop or forest management) and epistemic uncertainty (due to imperfect knowledge within models) will be analyzed at various levels through multi-model and multi-scenario approaches and appropriate statistical analysis. Results of the uncertainty analysis will be used as an input for modeling anticipative adaptation decisions in the economic models.
In terms of methodology, the main idea of the project is to rely on well-known models (global vegetation models, agronomic and forest models, economic models) and on published experimental data, and profit from existing methods (climate downscaling, meta-analysis, indicator reckoning...) and databases developed within the framework of previous projects on climate change impacts, in an integrated and coordinated way.

ORACLE is a true multi-disciplinary project that brings together climatologists, crop and forest scientists, economists, hydrologists and statisticians who have an experience in climate change issues at various scales.

Enhancing Capacities of the AgMIP South Asia Regional Teams through Capacity-Building Workshops and Knowledge-Sharing Platforms

Guntuku Dileepkumar et al.
Poster position: B2

Guntuku Dileepkumar, Dakshina Murthy Kadiyala, S. Nedumaran, Piara Singh, Raji Reddy, P Paramasivam, V Geethalakshmi, B Gangwar, N Subash, Ashfaq Ahmad, Lareef Zubair, S.P. Nissanka, V Sumanthkumar, Cynthia Rosenzweig, Jim Jones, John Antle, Carolyn Mutter

Agricultural systems are sensitive to extreme climatic events such as droughts, floods, delayed onset of monsoon, intermittent dry spells, heat and cold waves. The impact of these events is felt by regional agricultural systems differently based upon their climate, environment and socio economic conditions. Although there are many initiatives in progress to address the impacts of climate change all over the world but there are very few focusing on analysing impacts of climate variability and change through a transdisciplinary effort that consistently linking state-of-the-art climate scenarios to crop and economic models. The Agricultural Model Intercomparison and Improvement Project (AgMIP) is such initiative at global level linking climate, crop, and economic modeling communities with cutting-edge information technology to produce improved crop, and economic models and the next generation of climate impact projections for the agricultural sector.

The AgMIP South Asia Coordination Research Team (SA-CRT) ensures enhancing capacities of South Asia AgMIP Regional Research Teams in coordination with AgMIP Global team. The main goals of AgMIP South Asia CRT team are (1) enhance capacities of the multi-disciplinary research teams throughout the region and prepare them for integrated assessments of climate change impacts and adaptations (2) helps in designing workshops to publish the results of the integrated assessments that each research team has put together during the

project. In addition, the SA-CRT also aims to develop knowledge-sharing platforms so as to facilitate learning exchanges among and across the various AgMIP regional teams of South Asia and also ensure the national systems and various stakeholders utilizing the benefits of AgMIP research results.

In this paper the authors present the innovative capacity building and knowledge sharing platforms designed during the project period and their implications to meet the goals and objectives of AgMIP.

Enhancing Model Reuse via Component-Centered Modeling Frameworks: the Vision and Example Realizations

Marcello Donatelli et al.
Poster position: D11

Marcello Donatelli[1], Iacopo Cerrani[2], Davide Fanchini[2], Davide Fumagalli[2], Andrea Emilio Rizzoli[3]
[1] CRA-CIN, Consiglio per la Ricerca e Sperimentazione in Agricoltura, Bologna, Italy
[2] JRC IES, European Commission, Ispra (VA), Italy
[3] Dalle Molle Institute for Artificial Intelligence, Manno, Switzerland

Model frameworks have represented a substantial step forward with respect to monolithic implementations of biophysical models. However, the diffusion of such frameworks, as model development environment, beyond the groups developing them has been very modest. The reusability of models has also proved to be modest. The reason for the latter was attributed also to the lack of standardization toward few frameworks. Emphasis has been placed on the framework and even new implementations of models have been made targeting a specific framework, likely assuming that the reusability of the model unit would have been directly proportional to the quality of the framework. In any case, the goal of several projects has been to make available the framework. Developers in the operational arena, but even in research, have reacted by developing their own framework. Still, the problem of model reuse has been largely unsolved; estimating that increasing the flexibility for reuse would have added a costly overhead, in terms of both complexity and possibly as lack of efficiency in the operational use. The focus on frameworks has made software architects overlooking on the requirements of reusability per se of model units. The component oriented programming paradigm allows targeting intrinsic reusability of discrete model units, and makes room for enabling advances functionalities in simulation systems. This paper firstly present the abstract architecture of a component oriented framework articulated in independent layers: Model, Composition, and Configuration. The Application layer may link to any of these, to develop from simple console applications to sophisticated MVC applications. Proofs of concept are presented for each layer, including the BioMA framework of the European Commission used for agriculture and climate change studies.

Estimating Impact Assessment and Adaptation Strategies under Climate Change Scenarios for Crops at EU27 Scale

M. Donatelli et al.
Poster position: A1

M. Donatelli[1], A.K. Srivastava[2], G. Duveiller[2], S. Niemeyer[2]
[1] CRA-CIN, Consiglio per la Ricerca e Sperimentazione in Agricoltura, Bologna, Italy
[2] JRC IES, European Commission, Ispra (VA), Italy

Policy makers at European and national level demand for estimates of potential vulnerability of agricultural production. Estimates are requested specific to province level, and articulated for crops. The base of such estimates is the biophysical representation of crop responses both under conditions of no adaptation, and exploring the level of adaptation which could be acted on autonomously by farmers. However, producing such estimates poses significant challenges due to the usability of climate inputs to simulation models, to reliability and completeness of data, to the level of abstraction to be chosen, and to

technological aspects. This study provides an impact assessment of climate change scenarios on agriculture over EU27 focused on the time horizons of 2020 and 2030 with respect to a baseline centered on the year 2000. Potential and water-limited yields are simulated for 3 priority crops (wheat, rapeseed and sunflower) over a 25 by 25 km grid using the CropSyst model implemented within the BioMA modelling platform of the European Commission. Input weather data are generated with a stochastic weather generator parameterized over RCM-GCM downscaled simulation from the ENSEMBLES project, which have been statistically bias-corrected. Two realizations of the A1B emission scenario within ENSEMBLES are used, based on the HadCM3 and ECHAM5 GCMs, which respectively represent the "warmer" and "colder" extremes in the envelope of the ensemble with regard to the air temperature trends, and different with respect to rainfall patterns. Alleviating the consequences of unfavorable weather patterns is explored by simulating technical operations which can be acted on by farmers, highlighting the limits of autonomous adaptation, hence estimating potential vulnerability hotspots. Data are presented focusing on the difference between the baseline chosen and the 2020 and 2030 time horizons. Both data (accessible via web services) and the simulation platform are available for non-commercial use.

The Global Gridded Crop Model Intercomparison (GGCMI)

Joshua Elliot et al.
Poster position: D5

Joshua Elliott[1], Christoph Muller[2], and Delphine Deryng[3]
[1] University of Chicago, Argonne National Lab, and Columbia University
[2] Potsdam Institute for Climate Impact Research
[3] University of East Anglia

Initial results from the 2012 AgMIP/ISI-MIP Fast-Track assessment indicate the potential of global gridded crop model simulations and the need to further improve understanding of mechanisms, assumptions, and uncertainties of model design and execution; these are best addressed in a coordinated model intercomparison project at continental and global scale. In Spring 2013, we developed a new set of protocols for the GGCMI, which will run for 3 years and include 3 overlapping phases of increasing duration: 1) Historical simulation and model evaluation, 2) Analysis of model sensitivity to CTWN (carbon, temperature, water, and nitrogen), and 3) Coordinated regional and global climate assessment.

In this poster we summarize the protocols for the three phase project and present preliminary results from Phase 1 of the GGCMI: Historical simulation and model evaluation. In this stage, models are being run using various observation and reanalysis-based historical weather products so that they can be evaluated over the historical period globally and in various key interest regions. The project currently includes ~18 modeling groups from 11 countries, along with several other major data partners, and simulations are being performed over the Summer and Fall of 2013.

The 2012 AgMIP/ISI-MIP Fast-Track Assessment

Joshua Elliot et al.
Poster position: D6

Joshua Elliott[1], Christoph Muller[2], Delphine Deryng[3], Jerry Nelson[4], Franziska Piontek[5], and Cynthia Rosenzweig[6]
[1] University of Chicago, Argonne National Lab, and Columbia University
[2] Potsdam Institute for Climate Impact Research
[3] University of East Anglia
[4] University of Illinois at Urbana-Champaign
[5] Potsdam Institute for Climate Impact Research
[6] NASA GISS

In 2012 AgMIP led a Global Gridded Crop Model (GGCM) Intercomparison Fast-Track project in coordination with the PIK-led Inter-Sectoral Impacts Model Intercomparison Project (ISI-MIP). This fast-track included 7 GGCMs and updated the state of knowledge on climate

change vulnerabilities and impacts using modern global high-resolution models driven by climate model output from CMIP5. This fast-track culminated with the January 31st submission of 6 papers to a PNAS special issue, of which 5 are accepted or are in revision (3 accepted in time to meet deadlines for inclusion in IPCC AR5). In this poster we summarize each of these papers along with key findings from the 2012 Fast-Track assessment.

Evaluating the utility of dynamical downscaling in large-scale yield assessments

Michael Glotter et al.
Poster position: D7

Michael Glotter, Joshua Elliott, Alex Ruane, and Elisabeth Moyer

Because agricultural yield is highly sensitive to climate variability, yield projections require high spatial and temporal resolution weather products. Recently, multiple projects have combined GCM output with regional climate model (RCM) simulations to produce fine-scale (dynamically downscaled) climate projections to drive climate impact models. We investigate here whether these computationally intensive practices improve or affect large-scale crop yield estimates under future climate change. We drive a parallelized version of the DSSAT crop model for the continental United States with climate products from the NARCCAP regional climate model comparison project, using different GCMs both with and without dynamical downscaling. We find that once applying a relatively simple (but necessary) bias correction, there is little significant difference between crop yields whether driven by simply interpolated GCM output or by dynamically downscaled climate. Our results suggest that computationally intensive downscaling practices likely lend little additional value in agricultural impact applications. Yield projections under climate change may instead benefit most from improved observational climate data, especially in the developing world where data is scarce and modelers are often forced to rely on reanalyses (models nudged by observed atmospheric data). Reanalysis model output has significant flaws, however, and initial results suggest that observed precipitation is necessary for accurate agricultural yield estimates. Improving precipitation measurements in the developing world may be a critical part of estimating future food supply under climate change.

Climate scenarios for driving AgMIP models

Arthur Greene
Poster position: D8

Arthur Greene[1]
[1] International Research Institute for Climate and Society, Earth Institute at Columbia University, Palisades, New York, USA

We present a method for the generation of stochastic simulations on "near-term climate change" (i.e., decadal) time horizons, designed for driving models participating in AgMIP. In the absence of skillful decadal forecasts (particularly over land regions), such simulations provide a useful means of characterizing climate uncertainty and modeling its propagation through agricultural and ultimately, economic systems. The method involves the combining of information from various sources, including global climate models, local observational records and current research results. The climate models provide large-scale and long range information on climatic trends, while local observational records are employed for the characterization of higher-order variability. Both parametric and nonparametric techniques are employed in the merging of information. Example simulations are provided for selected regions, and issues that arise in simulation generation are described.

Climate change adaptations for crop-livestock systems in semi-arid Zimbabwe

Sabine Homann-Kee Tui et al.
Poster position: B15

Sabine Homann-Kee Tui[1], Patricia Masikate[1], Katrien Descheemaker[3], Lieven Claessens[2], Olivier Crespo[4], Andre van Rooyen[1], Roberto Valdivia[5]
[1] International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, www.icrisat.org), PO Box 776, Bulawayo, Zimbabwe, and [2] PO Box 39063, Nairobi, Kenya
[3] Wageningen University, Plant Production Systems Group, Wageningen, The Netherlands
[4] University of Cape Town, Climate Systems Analysis Group (CSAG), Cape Town, South Africa
[5] Oregon State University, Corvallis, Oregon

We present preliminary results of the Crop-Livestock Intensification Project (CLIP), answering AgMIP's three core questions: Potential impact of climate change (CC) on future agricultural systems and economic impacts of CC adaptation strategies. We focus on smallholder crop-livestock systems in semi-arid Zimbabwe. Maize is the predominant crop, with low yields (average 650kg/ha). Livestock productivity is also low; dry season feed shortages are major bottleneck. Two adaptation strategies were compared: 1. Crop intensification through fertilizer applications (0, 18 and 52 N kg/ha), 2. Systems shift towards livestock by introducing maize-mucuna rotation.

Climate simulations between current (1980-2010) and mid-century climate scenarios (2040-2070), for 5 selected GCMs project increasing temperatures (+2 - +3.3°C), but future rainfall is uncertain. Crop simulations (APSIM) suggest that maize yields can decrease by more than 20%, fertilizer and mucuna can offset these effects. Livestock simulations (LIVSIM) suggest marginal CC effects on livestock; fertilizer and maize-mucuna rotation can increase livestock productivity. The effects of GCMs on crops and livestock production are not consistent.

The TOA-MD economic ex-ante impact assessment, using household survey data and combined with RAPs developed through stakeholder consultation, indicates small CC effects on entire farms and heterogeneous farm populations in semi-arid Zimbabwe. Maize-mucuna rotation was identified as the more CC resilient adaptation strategy, providing higher farm net returns against less risk, compared to fertilizer applications. Economic benefits on the poor will however be minimal. More drastic systems shifts towards diversified and better integrated farming systems are required to sustain food security and move farms above poverty thresholds.

Anthropogenic Climate Feedbacks via Changes in Crop Productivity

Andrew D. Jones and William D. Collins
Poster position: A10

Andrew D. Jones[1], William D. Collins[1]
[1] Lawrence Berkeley National Laboratory

Climate change has the potential to impact agricultural productivity through multiple mechanisms. To the extent possible, farmers will respond to these changes by altering management practices and shifting the geographic distribution of various crops. Meanwhile, climate mitigation measures are placing unprecedented demands on agricultural systems for the provision of bioenergy. Such changes in land use and landcover are known to impact climate at both regional and global scales through changes in carbon storage and through direct physical consequences of landcover change. Yet, the current generation of 21st century climate projections (the CMIP5 RCP scenarios) do not account for dynamic land-use feedbacks. To address this gap, we are developing a new coupled model framework, the Integrated Earth System Model (iESM), which links the human decision making elements of an integrated assessment model with the physical and ecosystem components of a state-of-the-art global climate and earth system model.

Key to capturing agricultural land-use responses to climate change within this framework is the development of a new crop model for the Community Land Model (CLM) capable of

representing bioenergy crops. Preliminary results demonstrate the ability of this model to reproduce seasonal leaf area index dynamics for C4 perennial biofuel crops grown in North America. We have also conducted a sensitivity analysis to identify which parameters of the model yield meaningful changes in the simulation of climatically relevant variables such as surface energy and water fluxes, and soil carbon storage.

Modeling the impact of global warming on the sorghum sowing window in distinct climates in Brazil

Flavio Justino et al.
Poster position: C11

Flavio Justino[1], Marine Cirino Grossi[1], Camilo de Lelis Teixeira Andrade[2], Eduardo Alvarez Santos[1], Rafael Avila Rodrigues[1], and Luiz C. Costa[1]
[1] Departamento de Engenharia Agricola, Universidade Federal de Viçosa, PH Rolfs 36570 000, Viçosa, MG, Brazil
[2] Empresa Brasileira de Pesquisa Agropecuária, Centro Nacional de Pesquisa de Milho e Sorgo., Rod. MG 424, Km 45, Zona Rural, 35701970 - Sete Lagoas, MG, Brazil

F. Justino[1], M. Grossi[1], C. Lelis[2], E. Santos[1], R. Rodrigues[1] and L. Costa[1]

This poster presents recent result published by the European Journal of Agronomy.
http://www.sciencedirect.com/science/article/pii/S1161030113000919

This study aims to calibrate, and validate the CSM-CERES-Sorghum model and to investigate the vulnerability of sorghum yield for current (1982-1999) and future (2047-2064) epochs, by applying weather observations and climate outputs based on ECHAM, CCCma and GFDL models. Field experiments have been conducted in the experimental area of Janaúba and Sete Lagoas located in Minas Gerais State, Brazil. It has been found that the CSM-CERES-Sorghum model reasonably simulates crop phenology, crop biomass production, leaf area and yield components that are crucial to ensure the model reliability to reproduce in situ conditions. Comparison between the CSM-CERES-Sorghum results driven by the climate models and baseline observations shows that the ECHAM better reproduces the current observations. However, inaccurate results are found by utilizing the GFDL climate primarily due to lower precipitation values. This is found for both cities. Turning to future conditions, the simulations indicated that in Janaúba the average yields for current and future climate conditions were not statistically different, but in Sete Lagoas, there was a statistically significant increase in the sorghum productivity in the latter scenario. Moreover, it has been found that the simulations using the 52 sowing dates indicated that climate change modifies the grain yield projecting a delay in the most favorable planting date. According to the results the seeding of sorghum will very likely be held later in both cities.

Big Data for Big Solutions: Eddy Flux, Mesonet and C Sequestration

Vijaya Gopal Kakani et al.
Poster position: D13

Vijaya Gopal Kakani[1], Kundan Dhakal[1], Pradeep Wagle[1]
[1] Department of Plant and Soil Sciences, Oklahoma State University, Stillwater, OK

Bioenergy holds potential to positively contribute to economic and environmental well-being at farm and global scale. Quantification of C sequestration by bioenergy cropping ecosystem can be of great importance as measured ecosystem level CO2 fluxes can be extrapolated to estimate the regional carbon balance and simulate future atmospheric CO2 concentrations. Eddy flux systems provide continuous data on crop CO2 and H2O response to its environment. Weather networks such as Mesonet (www.mesonet.org) in Oklahoma provide high quality environmental data across the state. A combination of eddy flux and Mesonet data streams can provide estimates of regional C sequestration. The objectives of the study were to

(1) characterize the effects of key environmental factors on daytime NEE and to explore the underlying mechanisms, (2) identify potential switchgrass production areas across the State of Oklahoma, (3) conduct seasonal (April to August) spatial modeling of net ecosystem exchange (NEE) of C across potential switchgrass production area. Study window was limited to the active growing season. Potential switchgrass production areas in Oklahoma were identified from the USDA-NASS Cropland Data Layer (CDL). Mesonet data was checked thoroughly and processed to calculate 30-minute average values. Temperature response curves were developed for NEEsat, apparent quantum efficiency (AQE), day and night respiration based on eddy-covariance measurements at Chickasha, OK in 2011. The 30 min NEE values were generated as a function of NEEsat, PPFD and AQE for entire Oklahoma. The results of this study are useful for the modeling community to develop, improve, and validate the models for global climate change studies.

CropBASE: an integrative decision support platform for underutilised crops across research value chains

Asha S. Karunaratne et al.
Poster position: C10

Asha S. Karunaratne[1,2], Sayed Azam-Ali[1], Sue Walker[1]
[1] Crops For the Future Research Centre (CFFRC), c/o University of Nottingham, Malaysia Campus, Semenyih, Selangor, Malaysia
[2] Faculty of Agricultural Sciences, Sabaragamuwa University, Belihuloya, Sri Lanka

CFFRC is the world's first centre for research on underutilised crops for food and non-food uses. From its headquarters near Kuala Lumpur, Malaysia, CFFRC is building a global stakeholder alliance of education, public, private and civil society partners for research on underutilised crops. CFFRC activities focus around five research 'themes' that provide a 'Research Value Chain' of facilities and expertise on underutilised crops spanning plant genomics to applied social sciences.

CFFRC also has six research 'programmes' of which CropBASE provides an underpinning knowledge system and web-based platform for decision support and knowledge sharing on underutilised crops and their end uses. CropBASE will provide a quantitative basis to compare underutilised crop productivity and resource use efficiency with those of major crops and cropping systems under current and future climate scenarios. To provide such comparisons, CropBASE is developing interactive tools that integrate novel data on underutilised crops with geo-referenced information in existing and new databases.

The main analysis engine of CropBASE involves crop-climate modelling that introduce specific underutilised crops into recognised crop models (APSIM, AquaCrop, DSSAT) and link available climate databases within a geospatial information system framework. This poster presents a preliminary use-case scenario of bambara groundnut (an underutilised African legume) genotypes under baseline and future climate scenarios. By using contrasting African locations, interrogation methods are demonstrated that can identify genetically distinct material from matched climatic conditions to predict optimal selections of parental germplasm for breeding material suited to different locations and future climates.

Keywords: underutilised crops, productivity, crop models, climate change

The Influence of Shifting Planting Date on Cereal Grains Production under the Projected Climate Change

Dae-jun Kim et al.
Poster position: A11

Dae-jun Kim[1], Jae-hwan Roh[2], Jung-gon Kim[3], Jin I. Yun[1]
[1] Department of Ecological Engineering, Kyung Hee University, Yongin 446-701, Korea
[2] Rice Research Division, National Institute of Crop Science, Iksan 570-080, Korea
[3] Korean Wheat & Barley Industry Development Institute, Suwon 441-857, Korea

Yield reduction in major cereal grains seems unavoidable with the existing cropping systems under the projected climate change in Korea. Crop models were used to predict the effects of planting date shift on grain yields of rice, winter barley and soybeans at 64 agroclimatic zones in Korea. The shift of planting date by 7, 14, and 21 days before and after the recommended planting dates were incorporated in DSSAT experiment files to simulate growth, development and grain yields of major cereal crops. These included 3 rice cultivars representing early-, medium- and late- maturity groups, 1 winter barley and 1 soybean cultivars. Partial mitigation in yield reduction was found with earlier planting in the early maturing rice cultivar and with delayed planting in the late maturing rice cultivar under the RCP8.5 projected climate change in Korea. Additional yield increase in winter barley was expected by earlier planting treatments. Soybean showed a positive effect on grain yield with earlier planting. However, the rate was much lower than the case with winter barley and delayed planting caused yield reduction.

Modeling crop yields and yield gaps in Russia, Ukraine and Kazakhstan under climate change

Friedrich Koch et al.
Poster position: B9

Friedrich Koch[1,2]*, Florian Schierhorn[1]*, Alexander Prishchepov[1], Daniel Müller[1,3]
[1] Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO) Theodor-Lieser-Str. 2, 06120 Halle (Saale), Germany
[2] Helmholtz Centre for Environmental Research (UFZ), Permoserstraße 15, 04318 Leipzig/Germany
[3] Department of Geography, Humboldt-Universität zu Berlin Unter den Linden 6, 10099 Berlin, Germany
* Corresponding author (koch@iamo.de)

Global demand for agricultural products is projected to increase considerably. To satisfy the growing demand at low environmental costs is a key challenge for humanity. Russia, Ukraine, Kazakhstan can potentially contribute substantial additional production to global agricultural markets with their ample land reserves, fertile soils and high crop yield gaps. However, no comprehensive assessment of yield gaps in the region has been conducted to date. Of particular interest herein is the southern black soil (Chernozem) belt that possesses the highest production potentials in the region but is marred with frequently occurring droughts that are projected to increase further in terms of frequency and severity. The climatic conditions are in part also responsible for the prevailing low-input land management practices and low crop yields. We applied the process model SWAT to assess yield gaps throughout the region. SWAT includes plant growth and hydrology modules that are essential for large-scale physiological modeling in regions with volatile precipitation conditions because they allow to assessing climate, plant, soil and nutrient dynamics and simulating water management strategies. Our SWAT results for European Russia indicate yield gaps of 46-68% for spring and winter wheat, suggesting that land-use intensification, irrigation and re-cultivation of abandoned lands can potentially contribute to substantial production increases. We will further present how we will assess the impact of climate

change on crop yields at different spatial scales and which options exist to reduce yield gaps and to better adapt agricultural management practices.

Modelling Efforts and Integrated Regional Studies in FACCE MACSUR

Martin Köchy
Poster position: D10

Martin Köchy[1]
[1] Thünen Institute of Market Analysis, Bundesallee 50, 38116 Braunschweig, Germany

MACSUR is a knowledge hub (first phase 2012-2015) that gathers the excellence of research in livestock, crop, farm and trade modelling in Europe. It will illustrate for political decision makers how climate variability will affect regional farming systems and food production in the near and far future (till 2050). Furthermore, it will assess the associated risks and opportunities for European food security.

MACSUR develops multi-faceted approaches for integrated assessments in diverse regions like Europe. Aspects of heterogeneity include environment, structure, policy, climate, soils. An ensemble of crop and livestock models is benchmarked, inter-compared and coupled to both climatic and economic models in collaboration with AgMIP. In addition, MACSUR assesses options for crop rotations, mitigation measures, adaptation measures across scales, and considers national and farm economics.

Scaling, uncertainty analyses, and probabilistic assessment of impacts using calibrated models complement AgMIP activities.

In MACSUR regional pilot studies we assess crop production, livestock management, and farm economics in an integrated way, developing RAPs for Europe and involving stakeholders. First results compatible with AgMIP global scenarios will be presented at project meeting in April 2014.

Development and application of a weather data client for preparation of weather input files to a crop model

Chung-Kuen Lee et al.
Poster position: D1

Chung-Kuen Lee[1], Junhwan Kim[1], Kwang Soo Kim[2]
[1] National Institute of Crop Science, RDA, Suwon 441-857, Korea
[2] Department of Plant Science, Seoul National University, Seoul 151-742, Korea

Crop yield prediction has been made using a crop growth model that relies on four categories of input data including soil, crop, management, and weather. Most crop models are a single column model, which requires individual weather inputs for each site of interest. The objectives of this study were to develop a weather data service client that generates weather input files for a crop growth model and to examine its application to yield prediction at a national scale. The weather data service client was designed and implemented to download daily weather data from the web-based weather data service portal operated by Korean Meteorological Administration (KMA) and to generate weather input files for the ORYZA 2000 model. In total, 4950 input files were generated to predict rice yield in 2011 and 2012 using the weather data service client. To generate nearly 5000 weather input files, it would take more than a month for a skilled person to download weather data from the KMA database and to reorganize those data to the input data format for the ORYZA 2000 model manually. Using the weather data service clients, several hours were enough to generate all of the input files without error associated with manual preparation as well as with minimum effort and labor.

AgMIP Rice Team Activities

Tao Li et al.
Poster position: C6

Tao Li[1,‡], Toshihiro Hasegawa[2*,‡], Xinyou Yin[3*,‡], Yan Zhu[4,‡], Kenneth Boote[5,‡], Myriam Adam[6], Simone Bregaglio[7], Samuel Buis[8], Roberto Confalonieri[7], Tamon Fumoto[2], Donald Gaydon[9], Manuel Marcaida III[1], Hiroshi Nakagawa[10], Philippe Oriol[6], Alex C. Ruane[11], Françoise Ruget[8,12], Balwinder Singh[1], Upendra Singh[13], Liang Tang[4], Fulu Tao[14], Paul Wilkens[13], Yubin Yang[15], Hiroe Yoshida[10], Zhao Zhang[16], Bas Bouman[1,†]

[1] International Rice Research Institute, Los Baños, Philippines
[2] National Institute for Agro-Environmental Sciences, Japan
[3] Centre for Crop Systems Analysis, Wageningen University, the Netherlands
[4] National Engineering and Technology Center for Information Agriculture, Nanjing Agricultural University, China
[5] University of Florida, USA
[6] CIRAD, UMR AGAP, France
[7] University of Milan, Italy
[8] INRA, UMR1114 EMMAH, F-84914 Avignon, France
[9] CSIRO Ecosystem Sciences, Australia
[10] National Agriculture and Food Research Organization, Japan
[11] NASA Goddard Institute for Space Studies, New York, USA
[12] UAPV, UMR1114 EMMAH, F-84914 Avignon, France
[13] International Fertilizer Development Institute, Florence, Alabama, USA
[14] Chinese Academy of Sciences, Institute of Geographical Sciences and Natural Resources Research, China
[15] Texas A&M University, USA
[16] State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing 100875, China
* Corresponding: thase@affrc.go.jp; Xinyou.Yin@wur.nl † The leader of AgMIP Rice Team ‡ Members of leading group of AgMIP Rice Team. All other authors made equivalent contributions and are in alphabetical order by surnames.

AgMIP Rice Team was initiated under the umbrella of AgMIP at the kick of workshop at Bejing in 2011. It has thirteen crop modeling groups from Australia, China, France, Italy, Japan, Netherlands, CGIAR-IRRI and USA. The first annual meeting was held in December 2012 in International Rice Research Institute to share the achievements of the first-year implementation and to plan the activities for the next step. The second annual meeting will be held in Japan on 2 to 5 December 2013.

Over the last year, the team mainly focuses on the improvement of models for predicting rice response to CO_2 fertilization. We evaluated 12 rice crop models against multi-year FACE (Free-Air CO_2 Enrichment) experiments at two sites. Model simulation was implemented in two steps: 'blind' simulation, and simulation after model improvement or calibration. Groups in the team used own approaches to improve their model responses. The average responses and average predictions of all models on total above-ground biomass and grain yield were comparable or slightly improved before and after the model modifications. The differences between FACE measurements and predicting average of all models were less than 10% of measurements for both phases of simulation. However, some models might have uncertainty up to 20% of measurements. This exercise proved that current rice models are good enough for evaluating the effects of CO_2 elevation on rice growth and yield if ensemble model approach is used for the evaluation.

Fourth Annual AgMIP Global Workshop
Poster Abstracts - 21

Progress on the Maize Pilot Study

J.I. Lizaso et al.
Poster position: C5

J.I. Lizaso[1], J.L. Duran[2], K.J. Boote[3], S. Bassu[4], N. Brisson[#4], J.W. Jones[5], C. Rosenzweig[6], A. Ruane[6], M. Adam[7], C. Baron[8], B. Basso[9], C. Biernath[10], H. Boogaard[11], S. Conijn[12], M. Corbeels[13], D. Deryng[14], G. De Sanctis[15], S. Gayler[16], P. Grassini[17], J. Hatfield[18], S. Hoek[11], C. Izaurralde[19], R. Jongschaap[12], A. Kemanian[20], C. Kersebaum[21], N.S. Kumar[22], D. Makowski[4], C. Müller[23], C. Nendel[21], E. Priesack[10], M.V. Pravia[20], S-H. Kim[24], F. Sau[1], I. Shcherbak[9], F. Tao[25], E. Teixeira[26], D. Timlin[27], K. Waha[23], T. Tollenaar[28], S. Kumudini[28]

[1] Dep. Producción Vegetal, Fitotecnia, Technical University of Madrid, 28040 Madrid, Spain.
[2] Unité d'Agronomie, INRA-AgroParisTech, BP 01, 78850 Thiverval-Grignon, France.
[3] Dep. of Agronomy, P.O. Box 110500, Univ. of Florida, Gainesville, FL 32611.
[4] Unité de Recherche Pluridisciplinaire sur la Prairie et les Plantes Fourragères, INRA, BP 80006, 86600 Lusignan, France.
[5] Dep. of Agric. & Biol. Engr., P.O. Box 110570, Univ. of Florida, Gainesville, FL 32611.
[6] NASA Goddard Institute for Space Studies, Climate Impacts Group, 2880 Broadway, New York, NY 10025.
[7] CIRAD, UMR AGAP/PAM, Av. Agropolis, Montpellier, France.
[8] CIRAD, UMR TETIS, 500 rue J-F. Breton, Montpellier, F-34093.
[9] Dep. of Geological Sciences, Michigan State University, USA and Dept. Crop Systems, Forestry and Environ. Sciences, University of Basilicata, Italy.
[10] Helmholtz Zentrum München, Institut für Bodenökologie, Ingolstädter Landstraße 1, D-85764 Neuherberg.
[11] Centre for Geo-Information, Alterra, P.O. Box 47, 6700AA Wageningen, The Netherlands.
[12] WUR-Plant Research International, Wageningen University and Research Centre, P.O. Box 16, 6700AA Wageningen, the Netherlands.
[13] CIRAD-Annual Cropping Systems, C/O Embrapa-Cerrados Km 18, BR 020 - Rodovia Brasília/Fortaleza, CP 08223, CEP 73310-970, Planaltina, DF Brazil.
[14] Tyndall Centre for Climate Change research and School of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ, UK.
[15] Unité AGROCLIM, INRA, Domaine st Paul Site Agroparc, 84914 Avignon cedex 9, France.
[16] Water & Earth System Science (WESS) Competence Cluster, c/o University of Tübingen, 72074 Tübingen.
[17] Dep. of Agronomy and Horticulture, University of Nebraska-Lincoln, 178 Keim Hall-East Campus, Lincoln, NE 68503-0915.
[18] USDA-ARS National Soil Tilth Laboratory for Agriculture and the Environment, 2110 University Boulevard, Ames, IA 50011.
[19] Pacific Northwest National Laboratory and University of Maryland, 5825 University Research Court, Suite 3500 College Park, MD 20740.
[20] Department of Plant Science, The Pennsylvania State University, 247 Agricultural Sciences and Industries Building, University Park, PA 16802.
[21] Inst. of Landscape Systems Analysis, ZALF, Leibniz-Centre for Agricultural Landscape Research, Eberswalder Str. 84, D-15374 Muencheberg, Germany.
[22] Centre for Environment Science and Climate Resilient Agriculture, Indian Agricultural Research Institute, New Delhi, 110012, India.
[23] Potsdam Institute for Climate Impact Research, Telegraphenberg A 31, P.O. Box 60 12 03, D-14412 Potsdam.
[24] School of Environmental and Forest Sciences, University of Washington, Seattle, WA, USA 98195-4115.
[25] Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, 100101, China.
[26] Sustainable Production, The New Zealand Institute for Plant & Food Research Limited, Lincoln, Canterbury, New Zealand.
[27] USDA/ARS, Crop Systems and Global Change Laboratory, 10300 Baltimore avenue, BLDG 001 BARC-WEST, Beltsville, MD, 20705-2350.
[28] Monsanto Company
[#] N. Brisson passed away during the study in 2011.

Within the AgMIP Track 1 approach, we report the progress obtained by the Maize Pilot Team. Twenty three maize simulation models were included in the first study. Four sentinel sites, representing important zones of maize production, provided one-year site specific

measurements for model simulations: Lusignan, France (43.3° N), Ames, Iowa, USA (42°N), Rio Verde, Brazil (17.5° S), and Morogoro, Tanzania (6.5° S). For each site, 30-year of historical daily weather data were provided. Baseline weather was modified by changing maximum and minimum temperatures and [CO_2] levels. Simulations of baseline and modified weather in single factor series and in several combinations were obtained. Modelers were supplied sequentially with two levels of input information, low (only soil, phenology, and management), and high (initial conditions and time series of soil and crop measurements). In spite of simulated yield variability, the model ensemble accurately captured actual yields even with low information. Ensembles of 8-10 models would reduce substantially yield variability. Temperature increase had much larger and consistent response than CO_2 elevation in simulated yields. Higher temperatures also shortened life cycle of current cultivars, with small variability. Raising CO_2 levels resulted in higher yields and reduced crop transpiration, with largest variability at the highest simulated [CO_2]. The maize team has also been developing an improved maize model under the leadership of M. Tollenaar, from Monsanto. The new public maize model, AgMaize, will incorporate the best available algorithms simulating crop phenology, leaf area, photosynthesis, respiration, C partitioning, and N dynamics, and will have a modular structure adaptable to several modeling systems.

An Integrated Assessment of Climate Change Impact on Crop Production in the Nioro du Rip Basin of Senegal I: Crop Modelling

D.S. MacCarthy et al.
Poster position: B3

D.S. MacCarthy[1], M. Diancoumba[1], B.S. Freduah[1], S.G.K. Adiku[1], A. Agali[2], I. Hathie[3], J. Lizaso[4], D. Fatondji[5], M. Adams[6], L. Tigana[7], E. Koomson[1], P.C.S. Traore[5], S. Traore[2], J. Amikuzuno[8], J.B. Naab[9], D.Z. Diarra[10], B. Sarr[2], O. N'diaye[11], M. Sanon[7]
[1] University of Ghana
[2] AGHRYMET, Niger: Centre National d'Agro-Hydro-Météorologie du Niger
[3] IPAR, Senegal:Initiative Prospective Agricole et Rurale
[4] Technical University of Madrid, Spain
[5] ICRISAT Mali : International Crops Research Institute for the Semi-Arid Tropics
[6] CIRAD : Centre de Coopération Internationale en Recherche Agronomique pour le Développement
[7] INERA, B. Faso : Institut de l'Environnement et de Recherches Agricoles
[8] UDS, Ghana : University of development studies
[9] SARI, Ghana: Savanna Agricultural Research Institute
[10] METEO Mali
[11] ACACIM, Senegal :Agence Nationale de l'Aviation Civile et de la Météorologie

The economy of West Africa is highly dependent on agriculture which contributes between 40 to 60 % to gross domestic product and is home to about 300 million people. Crop production is largely dependent on natural weather which is increasingly becoming erratic. Projected climate change shows an increasing temperature trend and possibly a decline in rainfall, posing a major threat to agriculture productivity in the sub-region. This study aimed at assessing the future productivity of the major crops in Nioro, using two crop models and projected future climate data from five General Circulation Models (GCMs). DSSAT and APSIM models were calibrated with experimental data and validated with data collected from 220 farms in a socio-

economic survey. With the aid of the QUADUI, which is an innovative desktop utility, the effect of climate change with and without adaptation on the yields of millet, maize and peanut were simulated for 220 farms using multi-year baseline (1980-2009) and mid-century future (2040-2069) climate projections of five GCMs namely: E (CCSM4), I (GFDL-ESM2M), K (Had GEM2-ES), O (MIROC5) and R (MPI-ESM-MR).The yields of millet were negatively impacted by climate change using both crop models (i.e. 22 to 46% and 7 to 22% for DSSAT and APSIM, respectively). Similarly, simulated yields of peanut were lower with all GCM projected climates compared with baseline simulated yields. For maize, the responses of the GCMs were varied with GCMs R and K giving the lowest simulated yields. Introducing adaptation strategies however reduced the negative impact of climate change on simulated yields. This study indicates that the projected future climate will adversely affect crop production in Nioro. The negative effects can, however, be minimized with the use of improved crop ideotypes.

Modeling insect pest distribution under climate change scenarios

A. Maiorano et al.
Poster position: A15

A. Maiorano[1], I. Cerrani[2], D. Fumagalli[2], M. Donatelli[3]
[1] DISAFA, Università di Torino, Torino, Italy
[2] JRC IES, European Commission, Ispra (VA), Italy
[3] CRA-CIN, Consiglio per la Ricerca e Sperimentazione in Agricoltura, Bologna, Italy

This work describes potential impacts of climate change on a maize insect pest and a novel approach for predicting its distribution based on known physiological responses to specific weather factors. The model is based primarily on developmental responses, as these determine climates under which an insect can achieve a stable, adaptive seasonality. Cold tolerance during wintering was also modeled through an original approach based on the concept of lethal dose exposure. We simulated the potential winter survival, distribution, and phenological development of the corn borer Sesamia nonagrioides at three time horizons (2000, 2030, 2050), using the A1B IPCC scenario. Two modeling solutions for the simulation of winter survival were compared: the first using air temperature only as weather input (AirMS); the second taking into account the fraction of larvae overwintering in the soil, therefore considering also soil temperature (SoilAirMS). The survival model was linked to a phenological model. The SoilAirMS approach showed the best agreement, compared to the AirMS approach. Nevertheless the AirMS approach allowed identifying areas where the agronomic practices suggested for controlling S. nonagrioides should be considered ineffective. The projections to 2030 and 2050 suggested an overall slight increase of more suitable conditions for the S. nonagrioides in almost all the areas where it develops under the baseline. In these areas S. nonagrioides could become a new insect pest with a potential strong impact on maize. Differently from other works based on too simplistic approaches, results suggested that a warmer climate does not necessarily increases insect pest risks.

Modelling soil borne fungal pathogens of arable crops under climate change

L.M. Manici et al.
Poster position: A16

L.M. Manici[1], S. Bregaglio[2], D. Fumagalli[3], M. Donatelli[1]
[1] Dep. of Agricultural and Environmental Sciences - Production, Landscape, Agroenergy, University of Milan, Milan, Italy
[2] CRA-CIN, Consiglio per la Ricerca e sperimentazione in Agricoltura, Bologna, Italy
[3] JRC IES, European Commission, Ispra (VA), Italy

Soil-borne fungal plant pathogens, agents of crown and root rot, are seldom considered in studies on climate change and agriculture due both to the complexity of the soil system and to incomplete knowledge of their response to environmental drivers. A controlled chamber set of experiments was carried out to quantify the response of six soil-borne fungi to temperature,

and a species-generic model to simulate their response was developed. The model was linked to a soil temperature model inclusive of components able to simulate soil water content also as resulting from crop water uptake. Pathogen relative growth was simulated over Europe using the IPCC A1B emission scenario derived from the Hadley-CM3 global climate model. Climate scenarios of soil temperature in 2020 and 2030 were compared to the baseline centred on the year 2000. The general trend of the response of soil-borne pathogens shows increasing growth in the coldest areas of Europe; however, a larger rate of increase is shown from 2020 to 2030 compared to 2000 to 2020. Projections of pathogens of winter cereals indicate a marked increase of growth rate in the soils of Northern European and Baltic states. Fungal pathogens of spring sowing crops show unchanged conditions for their growth in soils of the Mediterranean countries, whereas an increase of suitable conditions was estimated for the areals of Central Europe which represent the coldest limit areas where the host crops are currently grown. Differences across fungal species are shown, indicating that crop-specific analyses should be run.

Assessing the effects of climate change on current smallholder-subsistence maize production in Southern Africa

Patricia Masikati et al.
Poster position: B16

Patricia Masikati[1], Sabine Homann-Kee Tui[1], Katrien Descheemaeker[2], Olivier Crespo[3], Andre van Rooyen[1]
[1] International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, www.icrisat.org), PO Box 776, Bulawayo, Zimbabwe
[2] Wageningen University, Plant Production Systems Group, Wageningen, The Netherlands
[3] University of Cape Town, Climate Systems Analysis Group (CSAG), Cape Town, South Africa

Smallholder farming systems constitute the majority of farmers in Southern African and major cereal production has been declining and if not stagnated in the last 2 decades while on the other hand demographics are on the increase leaving most people food insecure and malnourished. The precarious food shortage in the region is due to a combination of factors that include unfavorable climatic conditions, poor and depleted soils; environmental degradation; failed sectorial and micro-economic policies among others. Climate superimposed on the multitude of structural problems in the different countries in southern Africa where people are un prepared or have inadequate adaptation strategies climate change can easily set back possible developmental gains by affecting sectors such as agriculture, water resources and infrastructure among others. We have limited knowledge on the interactions between increase CO2 temperatures and precipitation variations and their combined effects on plant and animal development hence adding to uncertainties surrounding future crop and livestock production in mixed farming systems of southern Africa. We used two crop models (APSIM and DSSAT) to assess the impact of climate change on maize production in southern Africa. Results showed possible reduction of maize grain and stover yields and also that days to physiological maturity will be substantially reduced. Simulated effects were at varying levels across the countries due to biophysical and socio-economic issues. Country climate outlook (connected to crop modeling) is necessary in southern Africa where most countries are net importers of food. This would assist governments to prepare for suitable crop varieties and markets and also to prepare for food imports in time.

Critical temperature and sensitivity for white immature rice kernels

Yuji Masutomi et al.
Poster position: A12

Yuji Masutomi[1], Makoto Arakawa[2], Toyotaka Minoda[2], Tetsushi Yonekura[1], Tomohide Shimada[1]
[1] Center for Environmental Science in Saitama, 914 Kamitanadare, Kazo, Saitama 347-0115, Japan
[2] Institute for Paddy Rice Research, Agriculture and Forestry Research Center, 1372 Kubojima, Kumagaya, Saitama 360-0831, Japan

The incidence of white immature rice kernels (WIRKs) due to high temperatures during a ripening period has been recently a problem in the rice production of Japan. What is worse, future global warming will increase the incidence of WIRKs. The objective of the study is to quantify the critical temperature at which WIRKs begin to emerge (T_{cr}), and the sensitivity of the incidence to temperatures during a ripening period (S_t). This information would be helpful for estimating the incidence of WIRKs under current and future global warming conditions. In this study, we focus on a variety of rice "Sai-no-kagayaki," which is a rice variety bred in Saitama prefecture of Japan. In 2010, extreme high temperatures in summer caused the high incidence of WIRKs for the variety.

To quantify T_{cr} and S_t, we first propose a simple statistical model that includes T_{cr} and S_t as parameters. Then T_{cr} and S_t for each WIRK type are statistically quantified by experimental fields data. The results showed that T_{cr}s for milky-white and white-core kernels (MAC) and basal-white kernels (BSL) were about 25 degree, while T_{cr} for back- and belly-white kernels (BAB) was about 27 degree. Thus we found that MAC and BSL begin to emerge at a lower temperature than BAB. S_ts for BAB and BSL were about 10 %/degree, while S_t for MLK was about 2.5%/degree. Thus we found that BAB and BSL have a higher sensitivity to temperatures than MLK. These results suggest that we should pay the most attention to BSL, which has a low critical temperature and a high sensitivity to temperatures.

The Coordinated Climate-Crop Modeling Project (C3MP): Overview and Protocol Evaluation

Sonali McDermid et al.
Poster position: D3

Sonali McDermid[1], Alex Ruane[1], Nicholas Hudson[2], Cynthia Rosenzweig[1,2], and more than 60 C3MP Participants
[1] NASA Goddard Institute for Space Studies, New York, NY, USA
[2] Columbia Center for Climate Systems Research, New York, NY, USA

This poster will present an overview of the Coordinated Climate-Crop Modeling Project (C3MP), and an initial evaluation of C3MP protocols and results. C3MP is an on-going initiative that has already mobilized over 150 crop modelers from over 40 countries in a coordinated climate impacts assessment via the Agricultural Model Intercomparison and Improvement Project (AgMIP). Crop modelers are invited to run a set of common climate sensitivity experiments at sites where their models are already calibrated, and then submit their results to enable coordinated analyses for high-impact publications and data products. Of particular interest is the sensitivity of regional agricultural production to changes in carbon dioxide concentrations, temperature and precipitation (CTW), which in many cases is more robust across crop models and locations than are the absolute yields. By coordinating an investigation into these fundamental sensitivities, C3MP enables an investigation of projected climate impacts across a range of global climate models, regional downscaling approaches, and crop model configurations. Initial results submitted to C3MP have been compiled and the C3MP protocols and methodology has been evaluated. The C3MP emulation of yield responses to CTW changes has proved a close fit to simulated crop yields in most contributed locations. We show that the C3MP emulators display a plausible range of crop responses to changes in CTW, and we demonstrate the utility of these response surfaces when evaluating the impact of climate change conditions. As more crop modelers conduct these experiments, coverage will

increase in crops, models, farming systems, and locations to enable additional analyses of uncertainty in the agricultural impacts of climate change. By analyzing CTW sensitivities with today's climate as the origin, C3MP results will also facilitate the identification of key vulnerabilities and urgent interventions.

Integrated assessment of climate change and policy impacts on food security: a case study for protein crop supplies in Austria

Hermine Mitter et al.
Poster position: B14

Hermine Mitter[1], Franz Sinabell[2], Erwin Schmid[1]
[1] University of Natural Resources and Life Sciences Vienna, Institute for Sustainable Economic Development; Doctoral School of Sustainable Development
[2] Austrian Institute of Economic Research; franz.sinabell@wifo.ac.at

We present a methodology of how to use existing crop models with widely available economic data sets and established statistics in order to measure the impacts of climate change and policy adjustments on agricultural production systems and food security. Our case study is on a country in Europe but the method is transferable to other regions, policy scenarios and projections of climate change.

Approximately 75% of feed protein for livestock production in the EU is imported. During the last decade, European protein crop production has even diminished which raises concerns about supplies of protein in Europe. The recent reform of the Common Agricultural Policy (CAP) increases the competitiveness of protein crop production as farmers will be allowed to use cropland for producing legumes that would otherwise have to be set aside. We analyze two questions: (i) what is the likely impact of this policy change on supplies and land use, and (ii) how will climate change affect the competitiveness of protein crop production relative to other crops? We use Austria as case study, because it represents several European countries well-suited for protein crop production (the Danube basin).

We apply an integrated modeling framework to assess climate change impacts on level and variability of Austrian crop yields in combination with a policy reform, to analyze changes in national supply balances, land use, and to quantify economic and environmental effects of more intensive crop production. The bio-physical process model EPIC (Environmental Policy Integrated Climate) is applied to simulate, spatially explicit, annual crop yields and environmental outcomes for a historical period (1975-2005) and three climate change scenarios until 2040. Marginal opportunity costs of expanding protein crop production are estimated by the economic bottom-up land use optimization model for Austria BiomAT. The implications for crop supplies are quantified by using agricultural supply balances in a comparative static analysis.

Our results show that expected climate change and the policy reform are likely to raise domestic outputs of protein crops and the use of nitrogen fertilizer will decline.

Assessing Climate Change Impact on Rice Based Farming Systems in Sri Lanka and Adaptation Strategies using DSSAT and APSIM Models

S.P. Nissanka et al.
Poster position: B12

S.P. Nissanka[1], A.S. Karunaratne[2], W.M.W. Weerakoon[3], R. Herath[3], P. Delpitiya[3], B.V.R. Punyawardena[3], L. Zubair[4] and J. Gunaratna[5]
[1] University of Peradeniya
[2] University of Sabaragamuwa
[3] Department of Agriculture
[4] Foundation for Environment, Climate and Technology of Sri Lanka
[5] University of Rajarata

In line with AgMIP's attempts to develop adaptation to climate change for agricultural sector globally and regionally, the AgMIP-Sri

Lanka project investigated the climate change impacts on rice based farming systems and adaptation strategies, led by the Stakeholder Institutes of Department of Agriculture and Agricultural Universities.

Commonly cultivated rice varieties (Bg300, Bg358, Bg357) of a major rice growing region (Kurunegala) selected for the study, where rice production and other socio-economic information of farm families are available, were calibrated for both DSSAT and APSIM models using experimental data obtained from the Rice Research and Development Institute. Rice yield was simulated for 104 farmer fields for two growing seasons (major and minor) for the base years (2012-2013), historical period (1980-2010), and mid-century (2040-2069) for five GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, MPI-ESM-MR) of RCP-8.5 scenario. TOA-MD analysis was carried out using RAP strategies.

The base year RMSE for both seasons range around 1200-1300 kg/ha for observed (major-season 4289kg/ha; minor-season 3883kg/ha) vs simulated using DSSAT (major-season 4888kg/ha; minor-season 4410kg/ha). Compared to historical period, a significant yield reduction of 14%, 12%, 22%, 12%, 17% for the major-season and 31%, 30%, 42%, 28%, 35% minor-season, for the above five GCMs, was observed respectively. Among the adaptation strategies explored (adjusting planting window and short-duration variety), use of short-duration variety (Bg300) recovered yield losses significantly, especially in the minor-season where rainfall is relatively less and warmer. Similar trends were observed for APSIM model outputs as well. TOA-MD analyses revealed that the percentage losers are 68-70 and poverty level increase from 17% to 30% due to climate change.

Key words: Rice production, climate change impacts, food security, adaptation

Multi-model simulations for rice yield forecasts in Jiangsu (China)

V. Pagani et al.
Poster position: C13

V. Pagani[1], C. Francone[1], Z. Wang[2], S. Bregaglio[1], M. Donatelli[3], D. Fumagalli[4], F. Ramos[4], S. Niemeyer[4], Q. Dong[5], R. Confalonieri[1]
[1] Dep. of Agricultural and Environmental Sciences - Production, Landscape, Agroenergy, University of Milan, Milan, Italy
[2] Jiangsu Academy of Agricultural Sciences, People's Republic of China, Nanjing, Jiangsu, China
[3] CRA-CIN, Consiglio per la Ricerca e Sperimentazione in Agricoltura, Bologna, Italy
[4] JRC IES, European Commission, Ispra (VA), Italy
[5] Flemish Institute for Technological Research (VITO), Mol, Belgium

The Bio-physical Model Applications platform (BioMA) provides the opportunity to run multi-model simulations of crop growth and development against a common spatial database. Different crop models are characterized by their specific approaches to reproduce key physiological processes, thus producing varying crop responses to different environmental and climatic conditions. Within the EU-FP7 project E-AGRI on technology transfer of crop monitoring systems to developing economies the three crop models WARM, CropSyst and WOFOST were used to simulate rice growth in the Jiangsu province, China, in a warm (2006) and a cold (1999) season, using ECMWF weather data at 25 × 25 km resolution. The models performed similarly at field level with parameter sets calibrated on data of nine sites and two seasons. However, differing results of the crop growth simulations were obtained at the province level. While CropSyst-simulated biomass was driven mostly by air temperature gradients in the province, biomass simulated with WARM was dominated by radiation, with a more realistic response – especially in the warmest season – when air temperatures were higher than the optimum for the crop. WOFOST responded most strongly to high air temperatures, because unlike WARM it explicitly simulates the air temperature effect on respiration through a net-photosynthesis

approach. Facilitated through the BioMA platform the multi-model approach allowed for detecting and assessing the crop models' different peculiarities especially under anomalous and extreme weather conditions.

Integrated Assessment of Climate Change Impacts on Principle Crops and Farm Household Income in Southern India

Paramasivam Ponnusamy
Poster position: B13

Paramasivam Ponnusamy, Geethalakshmi Vellingiri, Lakshmanan Arunachalam,Sonali Mcdermid, Raji Reddy Danda, Dakshina Murthy, Mahendran Kandaswamy and Sunandini Prema

This study aims to assess the impact of climate change on agricultural production in southern India and its implications for farm household income and food security. Farm households in Tamil Nadu, Andhra Pradesh, and other Provinces excluding south-western Kerala of the Deccan Plateau are located in the rain-shadow of the Western Ghats. With meagre annual rainfall averaging 500 to 900 mm, the region is experiencing steadily decreasing soil fertility, growing dependence on groundwater for irrigation, falling ground water tables, and increasing fallow lands - characteristics that may be impacted by changes in long term climate trends. Agriculture sustains over half of the region's population. The study is carried out in Tamil Nadu (TN) and Andhra Pradesh (AP) States of South India. Household production systems in the region are characterized based on sources of irrigation in the region. Irrigated rice based cropping system in TN and both rain fed and irrigated maize based cropping systems in TN and AP are taken up for integrated impact assessment.

Crop models DSSAT and APSIM with climate parameter inputs from select RCP based (RCP 4.5 and 8.5) scenario downscales and management inputs from farm surveys are used to simulate base and climate impacted future yields with/without adaptations. Simulated yields are used for economic analysis to assess impacts on household incomes, employment and poverty. Following Shared Socio-economic Pathways (SSPs) under varying developmental assumptions, we attempt to develop Representative Agricultural Pathways (RAPs) to assess future trends and values for regional level management inputs through a participatory discussion process. Some of these RAPs based management variables are used in crop models along with future climate parameters to simulate future yields. Future farm characterizations derived from RAPs are combined with crop model simulated yields in economic tradeoff analysis using a Multi-Dimensional (TOA-MD) model for overall household impact assessment. The integrated analyses are replicated for a set of adaptation options to assess their efficacy in moderating climate change impacts on the rice and maize crops based production systems and households of the study region.

A biome-based analysis of current and future global crop yields

T.A.M. Pugh et al.
Poster position: D14

T.A.M. Pugh[1], S. Olin[2], A. Arneth[1]
[1] Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research (IMK-IFU), 82467 Garmisch-Partenkirchen, Germany
[2] Department of Physical Geography and Ecosystem Science, Lund University, Sölvegatan 12, S-22362 Lund, Sweden

Natural terrestrial vegetation occurs as part of functioning ecosystems whose composition and behaviour is dictated by the prevailing climatic conditions and other environmental factors, such as nutrient availability. Globally ecosystems can be broadly categorised into types, or biomes, according to the prevailing conditions and the dominant vegetation types therein. Throughout history humans have modified their surrounding environment, clearing natural ecosystems to provide raw materials and/or make space for other land uses, predominant among which is agriculture. These actions in themselves create new ecosystems which, excepting anthropogenic actions such as fertilisation and irrigation, will

function under largely the same environmental boundary conditions as the ecosystems they replace. These boundary conditions thus define the potential for how efficiently a new land-use can provide the service it was created for, such as food production. Using global observations of actual and potential yield we consider the yields of the major global staple crops wheat, maize and rice as a function of the natural biome in which they are grown. We compare the observed yields with those generated by a process-based global crop model, LPJ-GUESS. We then extend these biome-based yields into the future and consider how management processes such as irrigation and cultivar adaptation may influence the results. Finally we contrast the yield for each biome area with the carbon storage potential of the natural vegetation within that biome under present and future conditions and consider synergies and trade-offs between these two important ecosystem services.

Agricultural processes can substantially affect global climate forcing from CO_2

T.A.M. Pugh et al.
Poster position: D15

T.A.M. Pugh[1], S. Olin[2], A. Arneth[1]
[1] Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research (IMK-IFU), 82467 Garmisch-Partenkirchen, Germany
[2] Department of Physical Geography and Ecosystem Science, Lund University, Sölvegatan 12, S-22362 Lund, Sweden

Anthropogenic land-use and land-cover change has substantially altered fluxes of carbon between the terrestrial biosphere and the atmosphere, exerting a strong influence on global climate. Yet only relatively recently have anthropogenic land-use and -cover change been explicitly and widely represented in global terrestrial biosphere and Earth-System Models (ESMs). Typically such models represent all crops and pasture land (~35% of global land area in 2000) as grasslands. However, crops and pasture typically differ from natural ecosystems in terms of plant species, productivity, phenology, management, the annual growth cycle, and harvest; fundamentally affecting the amount of carbon stored by the terrestrial biosphere. We show that incorporating agriculture-specific processes in a global terrestrial biosphere model (LPJ-GUESS) can dramatically increase the carbon emissions resulting from land-use change by as much as 80% over period 1850-2005. Using climate forcing from an ensemble of ESMs we calculate the difference in terrestrial carbon accumulation over the period 1850-2100 under both moderate and extreme future climate pathways. We find that agriculture-driven differences in terrestrial carbon accumulation can result in a change in sign of the influence of the terrestrial carbon cycle on global climate from a net cooling to a net warming and influence global radiative forcing by as much as 0.5 W m^{-2}.

Projecting spring wheat yield changes on the Canadian Prairies: Resolutions of a regional climate model

Budong Qian et al.
Poster position: B7

Budong Qian[1], Ted Huffman[1], Hong Wang[2], Yong He[2], Jiangui Liu[1], Reinder De Jong[1]
[1] Eastern Cereal and Oilseed Research Centre, Agriculture and Agri-Food Canada, Ottawa, Ontario
[2] Semiarid Prairie Agricultural Research Centre, Agriculture and Agri-Food Canada, Swift Current, Saskatchewan

In addition to the uncertainty associated with crop models, climate scenarios are still a major source of uncertainty in projecting crop yield changes under climate change. Regional climate models (RCMs) are used as a tool for dynamic downscaling of climate scenarios from global climate models (GCMs) to regional scales for climate change impact studies. It is known that running an RCM is more expensive and time consuming at a higher resolution than at a lower resolution. Therefore, it is interesting to investigate how resolutions of an RCM might result in differences in the projected crop yield changes. We employed the CERES-Wheat model in DSSAT to simulate yield changes of

spring wheat at 13 locations across the Canadian Prairies, with climate scenarios from a Canadian Regional Climate Model (CanRCM4) driven by a Canadian Earth System Model (CanESM2) with forcing scenarios RCP4.5 and RCP8.5 at 25km and 50km resolutions. Bias correction and a stochastic weather generator referred to as AAFC-WG were used to develop future climate scenarios as input to the crop model. The results showed that when changes were averaged across the locations, whether 25km or 50km resolution CanRCM4 data were used, the projected yield changes were fairly consistent, with approximately a 20% increase under RCP4.5 and close to a 30% increase under RCP8.5, especially if AAFC-WG was used to develop climate scenarios. Spatial distributions of the projected yield changes were also similar for the two resolutions of CanRCM4.

Agricultural impacts of climate variability and change in Eastern Africa

K.P.C. Rao et al.
Poster position: B10

K.P.C. Rao[1], G. Sridhar[1], Mary Kilavi[2], Richard Mulwa[3], Siza Tumbo[4], Moses Tenywa[5], Araya Alemie Berhe[6] and Benson Wafula[7]
[1] International Crops Research Institute for the Semi-Arid Tropics, Addis Ababa, Ethiopia
[2] Kenya Meteorological Department, Nairobi, Kenya
[3] University of Nairobi, Nairobi, Kenya
[4] Sokoine University of Agriculture, Morogoro, Tanzania
[5] Mekerere Univeristy, Kampala, Uganda
[6] Mekelle University, Mekelle, Ethiopia
[7] Kenya Agricultural Research Institute, Embu, Kenya

Climate change impacts on smallholder agriculture was assessed in four Eastern African countries - Kenya, Ethiopia, Tanzania and Uganda – using the protocols and tools developed by Agricultural Model Inter-comparison and Improvement Project (AgMIP). In each country, a study area of the size of a district (about 150-200,000 ha) representing at least three major agro-ecological zones of the country and having about 50,000 households was selected. Household surveys were conducted to obtain the required input data for crop and economic models. In Kenya, the assessment covered five different agro-ecologies in Embu County. Projected future climate change scenarios for mid (2041-2070) and end (2071-2100) century were downscaled to four weather stations. Coarse outputs of 20 CMIP 5 General Circulation Models (GCMs) for Representative Concentration Pathways (RCP) 4.5 and 8.5 were downscaled by delta method to generate location specific future climate projections. Experimental data from maize grown under different nitrogen regimes for both long and short rain seasons were used to parameterize and evaluate crop simulation models DSSAT and APSIM. Maize yields of main food crop Maize under observed and future climates were simulated with APSIM and DSSAT crop models that were calibrated to simulate the locally relevant varieties and management practices. The diversity in the management employed by the farmers in the target region was captured by setting up runs for each of the 441 farmers involved in the survey. Analysis of bias-corrected and spatially downscaled scenarios indicated substantial changes in the climatic conditions at all locations. All GCMs predicted higher increase in minimum temperature compared to maximum temperature and most GCMs projected rainfall amounts are increasing from 10 to 150% in the region. Couple of GCMs projected reduction in rainfall amounts by 20%. Both APSIM and DSSAT predicted an increase in Maize yields in four out of the five agro-ecologies with projected climatic conditions mainly due to an increase in rainfall and projected temperature changes were within the crop optimum range. Within the agro-ecology, household-level impacts differed with management. High input systems (>35 kg of N/ha) were found to be more adversely affected compared to low input systems. The analysis helped in identifying a sub-set of management practices that enable smallholder to adapt and take advantage of the projected changes in climate.

Fourth Annual AgMIP Global Workshop
Poster Abstracts - 31

Climate Impact Estimates on C3MP's Worldwide Network of Crop Modeling Sites

Alex Ruane et al.
Poster position: D4

Alex Ruane[1], Sonali McDermid[1], Nicholas Hudson[2], Cynthia Rosenzweig[1,2], and more than 60 C3MP Participants
[1] NASA Goddard Institute for Space Studies, New York, NY, USA
[2] Columbia Center for Climate Systems Research, New York, NY, USA

We present preliminary projections of climate impacts from a network of 904 crop modeling sites contributed to the AgMIP Coordinated Climate-Crop Modeling Project (C3MP). At each site sensitivity tests were run according to a common protocol, which enables the fitting of crop model emulators across a range of carbon dioxide, temperature, and water (CTW) changes. When driven by global climate model projections, these emulators estimate probabilistic climate impacts across all sites for a range of scenarios and time periods. Preliminary results suggest consistently declining yields for irrigated and rainfed maize, with results comparable to (but slightly more pessimistic than) projections from an ensemble of global gridded maize models. Soybean and rice yield changes are relatively small; however wheat yields are projected to increase as some models demonstrate a beneficial reaction to initial temperature increases. Differences between C3MP results and comparisons with results from other AgMIP initiatives merit further study, so we invite you to join us at this workshop and to participate in C3MP in the months ahead.

An integrated analysis on Austrian agriculture - climate change impacts and adaptation measures

Martin Schönhart et al.
Poster position: B8

Martin Schönhart, Hermine Mitter, Erwin Schmid, Georg Heinrich, Andreas Gobiet

An integrated modelling framework (IMF) has been developed and applied to analyse climate change impacts and cost-effective adaptation measures in Austrian agriculture. Climate change is depicted by four contrasting regional climate model (RCM) simulations until 2050 and supplemented with three adaptation and policy scenarios. The IMF couples the bio-physical process model EPIC and the bottom-up economic land use model PASMA at NUTS-3 level considering agri-environmental indicators. Impacts from four RCM simulations show increasing crop productivity on national average. Changes in average gross margins at national level range from 0% to +5% between the baseline and three scenarios until 2040. The impacts are more pronounced at regional scale and range between -5% and +7% among Austrian NUTS-3 regions between the baseline and the three scenarios until 2040. Adaptation measures such as winter cover crops, reduced tillage and irrigation are cost-effective in reducing yield losses, increasing revenues, or in improving environmental states under climate change. Future research should account for extreme weather events in order to analyse whether average productivity gains at the aggregated level suffice to cover costs from expected higher climate variability.

Reimplementation and reuse of the Canegro model: from sugarcane to giant reed

T. Stella et al.
Poster position: C12

T. Stella[1], C. Francone[1], S.S. Yamaç[1], E. Ceotto[2], R. Confalonieri[1]
[1] Dep. of Agricultural and Environmental Sciences - Production, Landscape, Agroenergy, University of Milan, Milan, Italy
[2] CRA-CIN, Consiglio per la Ricerca e sperimentazione in Agricoltura, Bologna, Italy

The software design of simulation models often prevents their reuse and extension, forcing third-parties interested in modifying an available model to rewrite it from the beginning. This removes resources for model improvement, for the development of new models, and for the extension of their application domains, leading to the proliferation of software implementing models sharing large part of the algorithms. Component-oriented paradigm allows to overcome these limitations, favouring model extension and improvement, better maintenance, and massive code reuse. This study presents the application of these principles to the reimplementation of the sugarcane model Canegro, which led to the definition of an extensible, framework-independent component following the BioMA architecture. The innovation consists in the granularity and transparency of the implementation, as well as in architectural features that encourage the model analysis and extension. Each biophysical process (e.g., photosynthesis) is formalized through independent basic units (e.g., for light interception, energy conversion into assimilates, respirations), which can be easily substituted by alternative approaches. The advantages of this re-implementation lie (i) in the possibility of diffuse contributions to model development due to the independence from specific framework, and (ii) in the ease of reuse and modification of the model algorithms made possible by the fine granularity. The latter is here demonstrated through the extension of the component for giant reed (Arundo donax L.) simulation, a promising energy crop which shares several morphological and physiological features with sugarcane.

Strengthening Simulation Approaches for Understanding, Protecting and Managing Climate Risks in Stress-prone Environments across the Central and Eastern Indo-Gangetic Basin

Nataraja Subash et al.
Poster position: B11

Nataraja Subash, Harbir Singh, Babooji Gangwar, Guillermo Baigorria, Anup Das, Rajendra Dorai, Abeed Hossain Chawdhury, Andrew McDonald, Balwinder Singh and Sandeep Sharma

Climate change impacts are increasingly visible in Indo-Gangetic Basin of South Asia with greater variability of the monsoon. Direct and indirect impacts on agricultural production and thereby the food security and livelihoods of many small and marginal farmers, particularly in the more stress-prone regions of the central and eastern Indo-Gangetic Basin consist of India, Bangladesh and Nepal. Linking climate, crop and economic modeling will provide an insight into the integrated assessment of impacts of projected climate change on agricultural productivity of the region. The preliminary results of one site, Meerut (29° 4' N, 77° 46' E, 237 m ASL), of the Upper Gangetic region of the IGP, India based on AgMIP methodology is explained in this poster. To capture the yield variability, 76 farms were surveyed in 2009-10 to capture the variability. Sugarcane-wheat and rice-wheat are the most predominant cropping system followed in this region. The important observed variability of farms are viz., wide variability in dates of sowing - 17th October to 3rd January, Date of Harvest – 10th April - 17th May, Five cultivars – PBW223, PBW243,WL502, PBW343, UP232, No. of irrigations – 3,4 & 5, variability in N, P and K applications. In this preliminary analysis, we have calibrated the DSSAT and APSIM model for wheat crop. All GCMs predicted higher monthly mean maximum and minimum temperatures during the mid-century period 2040-2069 under RCP8.5 compared to baseline (1980-2010). All the five targeted GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, MPI-ESM-MR) predicted more or less same nature of projections. DSSAT simulated higher yields under projected climate

change scenarios compared to APSIM. This may be due to difference in sensitivity of DSSAT and APSIM with changes in CO_2 and temperature. The mean and variability scenarios are not different compared to mean only scenarios. TOA-MD results predict higher percentage of gainers (58-61%) with DSSAT as compared to APSIM (44-50%) under five climate scenarios. Overall, Climate change situation, APSIM predicts losses (1-12%) but DSSAT shows gains (15-21%) in mean net farm returns.

Software frameworks for crop model development and multi-purpose application

A. Topaj et al.
Poster position: C9

A. Topaj[1], S. Medvedev[1], V. Yakushev[1], A. Komarov[2], V. Shanin[2], V.Denisov[3]
[1] Agrophysical Research Institute, Grazhdansky pr., 14, 195220, Saint-Petersburg, Russia
[2] Institute of Physicochemical and Biological Problems in Soil Sciences, Institutskaya str., 2, 142290, Pushchino, Russia
[3] Klaipeda University, Herkaus Manto str., 84, LT-92294, Klaipeda, Lithuania

Nowadays, there is an obvious need for multi-purpose applications of crop models and, therefore, the model as a software product should satisfy requirements of various groups of stakeholders. The requirements formulated should serve as a blueprint for the design and implementation of the crop modeling software. Main focus of the contribution is made on collaborative model development including model decomposition issues and implementation of generic frameworks for multi-variant model use. Three main objectives are defined by the authors for such kind of systems:

- Multivariate simulation – run-time environment allowing the multiple running of the model with different input data in a batch mode.
- Unified shell – generic user interface that allows running various models inside of a single application via standard forms and use cases.
- Structural adaptation – ability to assembly the current implementation of simulation algorithm from the set of alternative pre-designed modules without recompilation of whole model.

The contribution presents a coherent view on mentioned problems based on results that have been elaborated in several research institutions of Eastern Europe. It contains short historical review, current state and prospective ideas for improvement of modeling infrastructure suitable to perform multi-factor computer experiments with crop or forest simulation models. In particular, authors present the original products APEX (Automation of Poly-variant EXperiments) and DLES (Discrete Lattice Ecosystem Simulator) and briefly compare them with analogous products and technologies (DSSAT, GUICS, CAPSIS, OpenMI).

Infrared Warming Affects Leaf Gas Exchange and Water Relations of Spring Wheat

G.W. Wall et al.
Poster position: A5

G.W. Wall[1], B.A. Kimball[1], J.W. White[1], and M.J. Ottman[2]
[1] USDA-ARS, Maricopa, Arizona
[2] University of Arizona, Tucson

Atmospheric CO_2 concentration is rising, which is predicted to induce global warming. Our objective was to characterize and quantify the ecophysiological response of spring wheat (Triticum aestivum L. cv. Yecora Rojo) and its microclimate to any potential concomitant rise in ambient temperatures associated with global change. A Temperature Free-Air Controlled Enhancement (T-FACE) apparatus with infrared heaters was employed to warm the canopy temperature of spring wheat by 1.5 and 3.0 °C during the diurnal and nocturnal periods, respectively. The experimental design was a completely randomized Latin square (3x3) consisting of three ecosystem warming treatments (control, heated, reference) in three replicates

over three planting dates (Mar., Sept., Dec.) during 2007 and 2008. Gas exchange properties and water relations of leaves as well as soil CO_2 efflux were measured. Compared with either the control or reference plots, in the heated plots, the uppermost sunlit leaf and those lower in the canopy had warmer leaf temperatures, higher net assimilation rates, and a decrease in internal water status - but they had comparable stomatal conductance and relative water content. The soil CO_2 efflux was greater in heated compared with reference plots. These results are useful for development and validation of temperature response functions in crop growth models that are being used to perform impact assessment on the sustainability of cereal grain crop production in a future high-CO_2 world.

AgMIP Water: Integrating Water Scarcity into Future Agricultural Assessments

Jonathan M. Winter et al.
Poster position: A8

Jonathan M. Winter[1], Alexander C. Ruane[2], Cynthia Rosenzweig[2]
[1] Dartmouth College
[2] NASA Goddard Institute for Space Studies

Agricultural productivity is strongly dependent on the availability of water, necessitating accurate projections of water resources, the allocation of water resources across competing sectors, and the effects of insufficient water resources on crops to assess the impacts of climate change on agricultural productivity.

This poster will detail AgMIP efforts at the interface of water and agriculture, including a pilot project that deploys a coupled hydrologic, water resources, and crop model over the Central Valley of California to explore the implications of future climate on irrigated agriculture; the recently held AgMIP - USDA Economic Research Service Water Workshop, which brought together over 35 leading scientists in climate, hydrology, water resources management, agronomy, and economics to develop strategies for improving the representation of water supply and demand in agricultural assessments; research in development; and opportunities to become involved in AgMIP Water.

New Drought Indices and Assessment in Drought Monitoring

Nana Yan and Bingfang Wu
Poster position: A7

Nana Yan[1], Bingfang Wu[1]
[1] Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China

Due to spatial coverage, data availability and cost efficiency, this paper focused on studying the potential to apply the satellite product to monitor drought. First is Standard Precipitation Index (SPI), which is widely used around the world for research and operational applications on meteorological and agricultural drought monitoring and early warning. SPI was designed to be calculated for any location that has a long-term precipitation record. Therefore, the accuracy of monthly precipitation data of TRMM (the Tropical Rainfall Measurement Mission) 3B43, was firstly investigated through comparison with rainfall data of forty ground stations in Hai Basin from 1998 to 2010.A single parameterized correction equation was presented to calibrate the TRMM rainfall data to formulate the series rainfall dataset of 30 year from 1981 to 2010. It was found that 3-month SPI was the best to depict the meteorological drought, which agreed well with the statistical drought information from 2000 to 2004. Second is Temperature-modified Anomaly NDVI Index (TANDVI) was improved based on the fact that NDVI was more affected by the accumulated temperature than precipitation in spring in the south plain of Hai Basin. The results indicated that the change of crop phenology would be an important factor which can bring the error on assessing the drought.

Irrigation and Rain Fed Croplands Separated Methodology Based on Remote Sensing

Hongwei Zeng et al.
Poster position: A6

Hongwei Zeng[1, 2], Bingfang Wu[1, 2, *], Nana Yan[1, 2]

[1] Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, 100101, China
[2] Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, 100101, China
[*] Corresponding: wubf@irsa.ac.cn

Irrigation croplands are the main water consumption of agricultural water resources, especially in arid and semi-arid basins. Due to lack of stabilized water supply, the yield of rain fed croplands tends to show large fluctuation than irrigation croplands in different year, such as wet season and drought period. Normalized Difference Vegetation Index (NDVI) and NPP could monitor effectively crop condition and estimate crop yield during crop growing season. Based on this hypothesis on yield fluctuation in different year, this work constructed NDVI and NPP time series of wet season and drought period, presented a threshold method to separate irrigated and rain fed croplands. Shijin irrigation district located at Plain of ZIYA River (PZYR) of Hai basin, winter wheat, maize, and cottons are the main crop types in this region. Due to rainfall deficit, during the winter wheat growing season (April to June); irrigation water supply is necessary for increasing crop yield. In order to estimate water supply stabilization and promote water resources management, this work used threshold of NDVI and NPP to illustrate the whole process on separating irrigation and rain fed croplands.

Key words: NDVI; NPP; Irrigation; Rain fed

The Impacts of Climate Change on Rice Farming Systems in North-Western Sri Lanka

L. Zubair et al.
Poster position: C15

L. Zubair, S.P. Nissanka, P. Agalawatte, S.C. Chandrasekera, C.M. Navaratne, J. Gunaratna, D.I. Herath, R.M. Herath, A. Karunaratne, B.R.V. Punyawardhene, W.M.W. Weerakoon, K.D.N. Weerasinghe, P. Wickramagamage, E. Wijekoon, Z. Yahiya

As a contribution to the AgMIP project, the impacts of climate on farming systems in the Kurunegala District in Sri Lanka were analyzed based on farmer surveys undertaken for the 2011 and 2012 seasons. Meteorological observations for 1980-2010 were subjected to quality checks and gap filling. These data were used to generate future climate scenarios for the farms using the 20 GCM's in the CMIP5 archive under the RCP8.5 scenario with further analysis restricted to 5 GCM's that are more skillful in the region. Calibration of DSSAT and APSIM crop modeling were undertaken with experimental observations in selected years in the two cultivation seasons. After further tuning, these crop models were used to simulate cultivation in the 2011 and 2012 seasons, the historical and mid-21st century periods. The climate projections shows a rise in maximum and minimum temperature for the future period by1.5 to 2.5 °C and a rise in rainfall by 1-3 mm/day for both seasons except for a drop in a couple of models. The DSSAT crop model simulations showed a drop in yield that ranged from 1.7% to 17% for the main season with a wider range of declines in the minor season. At two sites, the losses led to a slight increase in the fraction of farmers who were adversely affected while in other sites the analysis showed larger fractions were adversely affected. In the latter sites, the use of short-duration variety mitigated yield losses significantly. Work to refine methodologies and understand uncertainties is in progress.

Key words: Sri Lanka, Rice, CMIP5, DSSAT, APSIM, TOA-MD

AgMIP's mission is to improve substantially the characterization of world food security as affected by climate variability and change, and to enhance adaptation capacity in both developing and developed countries.

AgMIP coordination is located at the Columbia University Earth Institute Center for Climate Systems Research, 2880 Broadway, New York, NY 10025 USA
phone +1.212.678.5563 |
email info@agmip.org

Index

abscission, 317
ACE, AgMIP Crop Experiment database, 7, 84, 151, 155–158 160, 162, 163, 165, 166, 168
ACMO, AgMIP Crop Model Output database, 90, 91, 155–157, 160–163, 165, 166, 168
adaptation, 3, 4, 6, 16–20, 22, 28–35, 40–43, 61, 66, 70, 79, 80, 81, 9–95, 97, 103–106, 110, 115, 117, 121, 129, 133–135, 140, 141, 148, 153, 157, 164, 175–178, 184, 185, 195, 223, 227, 242, 301, 307, 312, 319, 320
aerosols, 227, 229, 235
Africa, 15, 20, 62, 119, 139
agent-based models, 244
aggregation, 5, 110, 113, 114, 118, 148, 155, 235, 268, 273
    disaggregation, 112, 114, 118, 244
AgGRID, AgMIP GRIDded Crop Modeling Initiative, 6, 179, 181, 197
AgMERRA, 51, 55, 56, 58, 59, 68, 184, 204, 209
AgMIP Maize Model Intercomparison, 185
AgMIP Regional Integrated Assessment Handbook, 31, 36, 42, 164
AgMIP Wheat Model Intercomparison, 185
agricultural development, 37, 132
agricultural economic models (AEMs), 107, 108, 243, 245
agricultural production, 9, 21, 132, 133, 135, 175, 223, 297
agricultural production system models (PSMs), 29, 108, 121, 164, 181, 185
agricultural regions, 54, 56, 123, 176, 206, 307, 319
agricultural systems, 18, 27, 29, 33, 35, 45, 49, 79, 92, 96, 97, 115, 122, 141, 195, 263
agroecological zones (AEZs), 244
albedo, 181
anthesis, 83, 247
AOGCM, Atmosphere-Ocean General Circulation Model, 239
aphids, 314, 315
APHRODITE model, 50
applications, 49, 96, 158, 163, 179, 267
APSIM, Agricultural Production Systems Simulator, 84, 88, 92–94, 156, 157, 168, 184, 207
AquaCrop model, 52, 156, 168, 207, 241
aquaculture, 33, 36
Argentina, 8, 206, 247, 248, 281, 284, 293
Argonne National Laboratory, 10
arid regions, 198
Asia, 62, 252
Asian citrus psyllids, 308
Asian soybean rust (*Phakopsora pachyrhizi* Syd. and P. Syd.), 306
assessments, 4, 6, 7, 10, 13, 106, 175, 179, 184, 370
assimilate sappers, 314, 315
assumptions, 87, 88, 132, 139, 148–150, 152, 153, 161, 175, 176, 184, 228, 287, 264, 287
atmospheric CO_2 concentration, [CO_2], 8, 18, 47, 68, 176, 195–198, 200–202, 210, 248, 283–286, 290–293, 297, 298, 314, 317
attainable yield, 312, 313, 318
Australia, 8, 168, 192, 193, 202, 206, 247, 248, 261, 280, 281, 284, 293
Austria, 183, 206, 280

bacteria, 299
bactericides, 319
Bambara groundnut, 205
Bangladesh, 126, 206
barley, 205
BAU, business-as-usual scenarios, 104, 117, 119
Bayesian approach, 242, 306
Belarus, 206
Belgium, 192, 193, 206
Benin, 206

bias correction, 49, 55–59, 63, 65, 68, 90, 122, 148, 240, 246, 287
bio-informatics, 13
biomass, 150, 302, 312, 316
blight (*Phytophthora infestans* (Mont.) de Bary), 304
Bolivia, 63, 67, 193, 206
Botswana, 206
Brazil, 192, 193, 206, 284, 293, 318
breeding, 69, 91, 155, 308
Burkina Faso, 206
Burundi, 7

C3MP, Coordinated Climate-Crop Modeling Project, 6, 9, 68, 195, 200, 204, 205, 207–211, 214–216, 246
calibration, 82, 95, 97, 149, 167, 180, 181, 203, 230, 241, 243, 250, 253, 263
calories, 178, 179
Cameroon, 206
Canada, 184, 192, 193, 206
canola, 205
canopy photosynthesis, 316, 317
carbon, 84, 87–89, 180, 182, 213, 316
CCAFS, Climate Change, Agriculture and Food Security Research Program of the CGIAR, 104, 119
cereal grains, 134, 300
CGIAR, Consultative Group on International Agricultural Research, 104, 300
chickpea, 205
China, 168, 184, 192, 193, 206, 281, 307
climate, 3, 29, 33, 34, 37, 39, 41, 42, 80, 91, 95–97, 108, 110, 113, 135, 148, 156, 160, 164, 167, 228, 233–235, 244, 298, 304, 306, 313, 318–320
climate change, 4, 6, 9, 11, 17–19, 21, 22, 28–30, 33, 36, 39, 40, 42, 45, 65, 79, 93, 94, 103, 105, 106, 110, 117, 120, 133, 134, 137–141, 164, 166, 175, 176, 180, 195, 213, 224, 226, 227, 234, 235, 242, 243, 246, 251, 283, 286, 287, 290–292, 297, 300, 301, 304, 307, 311, 312, 317–320
climate change impacts, 3, 5, 6, 9, 10, 12, 18–20, 30, 36, 41, 42, 53, 62, 79, 95, 103, 121, 129, 135, 175–178, 223, 243, 245, 320
climate change impact assessment, 36, 37, 39, 82, 114, 123, 179, 181, 185, 195, 213, 227, 234, 245, 263, 266, 306
climate models, 32, 51, 70, 80, 114, 148, 164, 215, 227, 229, 231, 234, 235, 237–240, 242, 250, 252, 263
climate scenarios, 9, 18, 49, 61, 64, 66, 70, 79, 112, 148, 157, 162, 164, 178, 283, 284, 287, 288, 290–292, 294, 304, 305, 312
climate sensitivity, 47–49, 61
climate systems, 45, 46, 49, 69, 227, 236, 239
climate variability, 21, 46, 49, 62, 65, 66
climate/weather data, 264, 267, 270, 273
CLIMEX model, 306
CMIP, Coupled Model Intercomparison Project, 10, 32, 46, 47, 50, 51, 62, 63, 67, 70, 90, 104, 185, 197, 215, 239
Colombia, 280
Columbia University, 4, 23
Committee on Earth Observing Satellites (CEOS), 70
commodities, 6, 11, 109, 110, 135, 244
communication, 225, 226, 245, 249
computable general equilibrium (CGE) models, 12, 243
CORDEX, Coordinated Regional Downscaling Experiment, 68, 185, 239
core climate impact questions, 28–31, 33, 37–42, 80, 89–91, 121
cost of production, 37, 90, 132, 134, 135, 319
cotton, 205, 241
    cotton–wheat, 141
cover cropping, 310
crop growth, 82, 83, 87, 96, 149, 241, 266, 283, 300, 314, 316, 317, 320
crop management, 80, 87, 263, 301
crop models, 4, 6, 8, 9, 12, 14, 19, 22, 38, 52, 55, 62, 68–70, 80–83, 85–89, 91, 92, 94–97, 115, 147–151, 153–156, 158, 160, 164–168, 175–177, 181, 195, 197, 199, 203, 205, 207, 209, 213, 215, 216, 225, 227, 229, 230, 233, 240–242, 244, 248, 253, 263, 266, 268, 273, 274, 283, 285–288, 290–293, 300, 301, 303, 311–315, 317, 318, 321
crop phenology, 82–84, 97, 150
crop physiology, 83, 266, 274, 303, 313, 320
crop production, 18, 81, 97, 133, 148, 196, 224, 234, 300, 311, 319
crop productivity, 175, 178, 300, 318, 320
crop rotations, 32, 85, 154, 158, 273, 303, 310, 320
crop yields, 14, 42, 86, 88, 97, 184, 234, 243, 251, 269, 283, 309, 313, 319, 320

CropGrow-NAU model, 156, 157, 168
cropping systems, 85, 88–92, 94, 97, 134, 176, 263, 300, 301, 308, 310, 319
CropSyst model, 156, 157, 168, 180, 183, 207
CSM, Cropping System Model, 104, 316
CSV, comma-separated values, format, 158–160, 166
cultivars, 82–84, 86, 87, 89, 91, 134, 148, 180, 181, 217, 229, 266, 309, 311, 312
cultivation, 82, 135, 175
Czech Republic, 206

data, 3, 4, 6, 10, 12–14, 17, 19, 20, 32–34, 41, 50, 55, 70, 83, 84, 87, 89, 90, 94, 95, 97, 103, 107–109, 113, 114, 122, 148, 149, 151, 154, 155, 157, 162, 163, 166, 167, 176, 230, 241, 253, 263, 266, 267, 305, 314, 316, 317
  database, 90, 96, 140, 150, 163, 167, 196, 197, 223
  datasets, 149–151, 246, 283
  data harmonization, 119, 147, 148, 151, 155, 156, 159, 161, 166, 168
  data interoperability, 96, 97, 148, 149, 154, 155, 158, 166, 167
  data schema, 147, 150, 151, 167
  data translation tools, 158, 161, 163, 164, 168
DAYCENT model, 183, 207
decision-makers, 4, 6, 16, 18, 28, 29, 36, 50, 69, 70, 121, 226, 227, 233, 245, 263
defoliation, 313, 316
delta scenarios, 52, 62, 63, 64, 66, 240
demand, 19, 108, 134, 177
Denmark, 193, 206, 280
developing countries, 3, 7, 19, 33, 53, 59, 297, 298, 319
development, 16, 19, 20, 22, 69, 80, 133, 134, 139
DevRAP tool, 115–118, 121, 131
dew-point temperature, 52, 63
DGVM, dynamic global vegetation models, 180, 183
dimensionality, 33, 113, 114
disaster risk management, 135
disease models, 302, 303, 306, 308, 309, 315, 318
diseases, 33, 81, 302–319
  disease hosts, 299, 300, 302, 303, 308–310, 320
DOME, Data Overlay for Multi-model Export, 87, 150, 152–154, 158–160, 163, 164, 166
downscaling, 49–51, 108, 113, 118, 215, 216, 229, 232, 239, 266
DRAINMOD model, 207
drought stresses, 134, 175, 297, 306, 317
dry matter accumulation, 317
DSSAT, Decision Support System for Agrotechnology Transfer, 51, 52, 83, 84, 88, 92–94, 155–157, 160, 168, 184, 203, 207, 243, 315, 319
  DSSAT-CERES-CROPSIM, 318
  DSSAT-CROPGRO, 316, 318

Earth Systems Science Partnership (ESSP), 300
East Africa, 18, 125, 126, 138
economics, 3, 17, 28, 29, 31, 33, 34, 36, 37, 41, 42, 50, 69, 79–81, 85, 89–91, 94, 95, 105, 108, 112, 119, 125, 132, 133, 135, 139, 166, 176, 177, 234, 243, 300, 310, 318
economic models, 12, 19, 31, 34, 50, 97, 108, 113, 121, 142, 155, 164, 167, 178, 195, 225, 227–229, 238, 242, 243, 253, 300, 301
ecosystems, 35, 175, 180, 302
education, 132, 135
Egypt, 206, 307
El Niño Southern Oscillation (ENSO), 304, 307
emissions, 103, 106, 110, 226, 235
  emission scenarios, 148, 306
empirical models, 180, 181, 183, 184, 304, 313, 317, 319, 320, 321
employment, 132, 134
energy, 56, 108, 135, 180, 312
ensembles, 50, 79, 80, 114, 147, 149, 150, 158, 162, 177, 226, 231, 233, 234, 238, 245, 253, 271, 273, 283, 286, 287
environment, 10, 39, 109, 149, 180, 269, 271, 273, 297, 302
EPIC, Erosion Productivity Impact Calculator, 109, 156, 157, 168, 180, 183, 184, 270
errors, 81, 166, 226, 227, 229, 230, 232, 241, 253, 263, 300, 306
ESM, Earth System Model, 104
Ethiopia, 193
Europe, 243, 252
evapotranspiration (ET), 52, 184, 312
experiments, 83, 84, 87, 89, 96, 97, 147, 152, 160, 167
extension, 85, 87, 121, 132, 134, 135

extreme events, 46, 49, 55, 68, 70, 115, 175, 229, 235, 298, 305, 306, 311

FACCE JPI, Agriculture, Food Security, and Climate Change Joint Programming Initiative, 269
Fall armyworm, 315
farm size, 22, 37, 40, 109, 120, 134, 135, 138
farm surveys, 33, 81, 85, 87, 89, 95, 148
farming systems, 17, 19, 33, 35, 36, 40, 41, 42, 80, 87, 95, 96, 109, 126, 132, 133, 137, 139, 141, 148, 150, 155, 185, 196, 263, 274, 303, 308, 310
  farms, 109, 120, 164, 266
FASOM, Forest and Agricultural Sector Optimization Model, 109, 243, 245
fertilizer, 20, 22, 32, 33, 68, 82, 89–91, 93, 94, 120, 121, 133, 135, 150, 152, 154, 155, 184, 185, 243, 288, 297, 299, 312, 313
field, 147, 148, 164, 232, 309, 319
  field experiments, 149–151, 159
Finland, 193, 206, 261, 280, 304
flood, 134, 175
fodder, 297
foliage temperature, 312
foliar plant pathogens, 310, 314, 316
food, 3, 79, 132, 134, 135, 178, 240, 244, 263, 297
food prices, 105, 176, 178
food production, 10, 177, 178, 224, 298, 300
food security, 3–7, 19, 21, 22, 29, 95, 122, 132, 134, 163, 166, 175, 263, 298
forage supply, 32
forestry, 243
France, 168, 183, 192, 193, 206, 261, 279–281, 284, 285, 293, 306
fungi, 299
fungicide, 311, 316, 317, 319
fuzzy logic, 118, 306

GAEZ-IMAGE model, 177
Gaussian probability distributions, 36, 285
GDP, gross domestic product, 104, 114
genetics, 82, 309, 312
Germany, 183, 192, 206, 261, 271, 272, 279, 280
GEWEX, Global Energy and Water Exchanges Project, 55, 203
GGCMs, global gridded crop models, 10, 11, 19, 68, 176, 179, 181, 185, 320
GGCMI, Global Gridded Crop Model Intercomparison, 7, 10, 179–185
Ghana, 206, 214
GHGs, greenhouse gases, 45, 46, 51, 61, 103, 105, 113, 197, 226, 229, 235, 273
GIS, geographic information systems, 302–304
github.com, 158
GLAM model, 207, 242
global climate models (GCMs), 11, 45, 47–49, 61, 63, 65, 66, 68, 69, 101, 103, 104, 107, 108, 113, 153, 176, 177, 195, 197, 224, 236, 238, 274, 276, 304, 305
global crop models, 5, 178, 213
global economic models, 5, 11, 32, 33, 42, 91, 119, 176, 244
GLOBIOM model, 109
government, 28, 120, 121, 133–135, 139
GPCP, Global Precipitation Climatology Project, 55
grasslands, 96, 202
Greece, 147, 168, 192, 206
grid cells, 268, 270–272, 320
growing season, 176, 181
Guinea-Bissau, 206

harvest, 52, 150, 213, 214, 312
heat stress, 68
high-altitude regions, 305
high-latitude regions, 46, 211
hindcasts, 228, 229, 253, 314
host plants, 299, 302, 310, 320
  host resistance, 308, 309
  host-pathogen models, 303
households, 18, 29, 33, 50, 109, 120, 134, 164, 319, 320
humidity, 53, 304
hunger, 298
HWSD, Harmonized World Soils Database, 148

IAMs, integrated assessment models, 103, 104, 107, 108, 114
ICASA, International Consortium for Agricultural Systems Applications, 151, 152, 154, 155, 163, 164, 166
IMPACT global economic model, 109, 119
impact assessment, 9, 19, 35, 37, 42, 49, 79, 103, 107, 108, 114, 115, 119, 124, 137, 142, 225–227, 242, 243, 246, 253, 268
impacts, 29, 30, 32, 34, 37, 41, 69, 70, 80, 120, 140, 141, 196, 246

impacts response surfaces, 68, 202, 209
imports, 132, 134
incentives, 39, 132, 134
income, 18, 20, 29, 108, 243
India, 7, 8, 92, 93, 125, 134, 168, 192, 193, 206, 214, 247, 248, 279, 280, 284, 293
indicators, 28, 119–123, 131
Indo-Gangetic Basin (IGB), 15, 62, 125, 134
Indonesia, 193, 206
infection, 318, 303
InfoCrop model, 156, 168, 207
information technology (IT), 4, 10, 12, 14, 32, 50, 51, 70, 84, 88, 90, 94, 95, 97, 163, 196
inputs, 109, 132, 134, 135, 141, 147, 148, 150, 155, 158, 160, 161, 163, 164, 179–182, 184, 185, 229–231, 240, 242, 243, 263, 266–269, 273, 287, 304, 312, 321
insect pests, 33
insecticides, 308, 319
integrated assessment, 27, 31, 80, 81, 92, 121–124, 243, 253, 301, 318
integrated crop, pest, and disease management, 319
intellectual property, 161, 162
interannual variability, 202, 271, 272, 306
interest rates, 132
Intergovernmental Panel on Climate Change (IPCC), 19, 181, 227, 237, 238, 249
Internal climate variability, 235, 239, 240, 251
International Benchmark Sites Network for Agrotechnology Transfer Project (IBSNAT), 151
International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), India, 162
interpolation, 235
investments, 121, 132, 133, 135, 139, 226, 230
Iran, 193, 206
irrigation, 20, 22, 32, 86, 89, 92, 94, 133, 135, 150, 154, 179, 181, 242
ISI-MIP, Inter-Sectoral Impact Model Intercomparison Project, 10, 176–178, 185
Italy, 192, 193, 206, 261, 280

Japan, 62, 63, 65, 66, 184, 192, 206
JSON, JavaScript object notation, 151, 158
JULES-Crop model, 180

K-strategists, 298
Kazakhstan, 206
Kenya, 18, 125, 133, 160, 192
key-value pairs, 152, 166
Korea, 193, 206

labor, 17, 132–134, 108, 141, 243
LAI, leaf area index, 316, 317
land, 108, 132, 133, 135, 239, 243, 244, 297
  land use, 12, 19, 34, 70, 106, 108, 109, 116, 185, 230, 235, 243, 245
  land-surface, 180, 237, 239
Latin Hypercube, 198
leaf spot (*Cercospora arachidicola*), 314–317, 319
lentil, 205
lesser cornstalk borer, 314, 315
Lithuania, 206
livelihoods, 15, 21, 34, 132
livestock, 17, 31, 33, 35, 36, 97, 109, 121, 140, 243
  livestock models, 6, 32, 36, 40, 41, 64, 108, 120, 228, 319
LPJ-GUESS model, 177, 180
LPJmL model, 177, 180, 183

MACSUR, Modelling European Agriculture with Climate Change for Food Security, 162, 246, 264, 269, 271
Madagascar, 206
maize, 11, 20, 88, 89, 92–94, 133, 135, 178, 179, 202, 205, 211, 241, 283, 285, 287, 288, 292, 294
Malawi, 139, 206
Mali, 206
management, 12, 18, 34, 81, 82, 84–87, 89–91, 93–97, 109, 112, 141, 147, 148, 150, 152, 153, 155, 164, 175, 176, 178, 180, 185, 229, 242, 273, 274, 300, 302, 308–310, 312, 319
manure, 85, 86
markets, 69, 109, 110, 121, 132–135, 243
maturity, 83, 247
Mauritania, 206
measurements, 53, 149, 151, 157, 197, 230
mechanization, 135
Mediterranean region, 248
MERRA, Modern-Era Retrospective Analysis for Research and Applications, 9, 56, 90, 203
metadata, 90, 91, 151–153, 155, 157, 158, 162, 166
meta-model, 283, 288, 292
meteorological data, 53, 54, 305
Mexico, 46, 206

microclimate, 303
Middle East, 206
millet, 205, 248
mitigation, 103, 105, 106, 109, 110, 175, 226
models, 5, 10, 13, 31, 32, 34, 36, 40, 49, 103, 108, 114, 116, 147–149, 152, 154, 157, 158, 166, 181, 182, 195, 199, 213, 214, 223–225, 228–230, 232, 233, 239, 242, 244, 246, 253, 266, 267, 273, 274, 305, 311
  model improvement, 13, 167, 197, 213, 227, 253
  model parameters, 33, 118, 121, 230, 232, 244, 263, 267, 306
  next-generation models, 6, 162, 163, 167
MONICA model, 270
monocrops, 309
monsoon, 62, 66, 238
Monte Carlo simulation, 231, 244, 245
Mozambique, 125, 132, 133, 139
multi-model ensembles (MMEs), 3, 6, 31, 87, 179, 182, 196, 217, 227, 231, 233, 234, 237, 242, 254
  multiple models, 151, 165, 231

Namibia, 125, 133
NARCCAP, North American Regional Climate Change Assessment Program, 50
narratives, 116, 117, 119, 121, 122, 141
NASA, 70
National Climatic Data Center (NCDC), 56, 58
natural resources, 112, 135
Nepal, 126, 130, 135, 141
Netherlands, 183, 247
New Zealand, 193, 206, 261, 281
Niger, 58, 59, 206
nitrogen (N), 11, 19, 83, 84–87, 89, 96, 154, 177, 180, 182, 203, 211, 269, 273, 286, 312, 313, 316
non-agricultural income, 28, 33, 36, 40, 46, 109, 120, 133, 135
non-linear programming models, 310
non-relational database architecture, 151
non-stationarity, 49
Northern Hemisphere, 305
nutrients, 167, 320
nutrition, 41

oilseed rape (*Brassica napus* L.), 306
Open Data Journal for Agricultural Research (*ODJAR*), 162
open-source projects, 158, 161
opportunity cost, 39, 40
orchards, 303
ORCHIDEE model, 180, 183
organic matter, 85, 86, 88, 154, 297
ORYZA2000 model, 156, 168
outputs, 132, 147, 148, 150, 151, 155, 158, 161, 162, 164, 177, 228, 240, 242, 244, 267, 268, 288

Pakistan, 116, 119, 125, 131, 134, 141, 142, 193, 206
Panama, 202, 206
parameters, 41, 50, 82, 86–88, 95, 96, 108, 109, 115, 117, 122, 142, 148, 150, 152, 154, 167, 177, 180, 226, 228–232, 234, 239, 241–244, 253, 266, 274, 286, 313
partial equilibrium (PE) economic models, 12, 108, 109, 176, 243
partitioning, 312, 317
pasture, 205
pathogens, 299, 301–305, 307, 308, 314, 315, 319
peanut, 205, 241, 248, 316
PEGASUS model, 177, 181
pests and diseases, 81, 82, 89, 109, 110, 120, 181, 195, 234, 253, 269, 298, 299, 301, 310, 312–320, 321
  pest and disease models, 313, 318
pesticides, 297
Philippines, 168, 206
Phoma stem canker, 306
phosphorus (P), 107, 181
photosynthesis, 180, 311, 312, 314–317
Phytophthora cinnamomi root rot., 304
plant pathology, 302
plant population, 18, 86, 93, 94, 300, 303
planting, 52, 150
  planting dates, 18, 89, 32, 166, 181, 250, 304
PNUTGRO model, 315
Poland, 206
policy, 4, 6, 16, 17, 37, 39, 41, 45, 70, 91, 105, 108–110, 112, 121, 122, 132–134, 137, 139, 141, 175
pollution, 135
population, 36, 39, 41, 92, 106, 108, 114, 133, 134, 225, 230, 235, 241, 287, 297
potassium (K), 181
potato, 63, 205, 300, 304

poverty, 18–20, 22, 29, 41, 132, 133, 135
precipitation, 45, 52, 53, 55, 56, 62–66, 68, 107, 175–198, 200–202, 251, 252, 284, 285, 287, 288, 293, 300
prices, 12, 34, 37, 42, 91, 109, 110, 116, 119, 135, 139, 175, 177, 244
PRISM model, 50, 59
private sector, 132, 133, 139, 160
probability, 65, 215, 236, 245, 248, 249, 287, 292
  probability distribution, 225, 226, 228, 230, 245, 286, 293
producers, 113
production, 108, 135, 141, 176, 179, 244, 312, 319
  production costs, 36, 121
  production inputs, 120, 243
production system, 30, 38, 39, 41, 90, 109, 119, 122, 130, 141, 318, 319
productivity, 29, 40, 42, 108, 112, 116, 132–135
profit, 132, 135, 244
Program for Climate Model Diagnostics and Intercomparison (PCMDI), 61, 62, 70
protocols, 8–10, 28, 31, 42, 43, 50, 69, 90, 94, 95, 97, 148, 161, 163, 175, 204, 234
pSIMS, Parallel System for Integrating Impact Models, 7, 184
  pAPSIM, 180, 183, 184
  pDSSAT, 177, 180, 183, 184
public sector, 118, 132, 134, 161
Punjab, 21, 134
pyranometer, 53

quadratic regressions, 199, 202
QuadUI desktop application, 158–163, 165
quality assessment and quality control (QAQC), 53

R software package, 61, 63, 67, 287
radiation-use efficiency (RUE), 180
radiative forcing, 236, 237
rainfall, 18, 65, 68, 94, 212, 283, 285, 286, 297, 303, 306, 311, 313, 314
rainfed crops, 92–94, 141, 178
rangeland, 140
REAP model (Regional Environment and Agricultural Programming), 245
regional climate models (RCMs), 49, 50, 68, 104, 107, 108, 238–240
regional economic models, 164, 166
regional integrated assessments (RIAs), 14, 17, 19, 20, 28, 31, 33, 34, 40, 47, 50, 59, 61, 68, 69, 87, 90–92, 94–96, 104, 106, 115, 118, 147, 148, 160, 163, 165, 167
regional research teams (RRTs), 125, 148, 168
regions, 83, 85, 89, 95, 110, 112, 123, 124, 132, 135, 140, 179, 196, 197, 232, 251, 253, 266, 273, 301, 304, 308, 311, 312, 320, 321
regression models, 285, 287, 312–314
relative humidity, 52, 55, 299, 313
representative agricultural pathways (RAPs), 5, 32–34, 37, 40, 42, 61, 80, 81, 91, 92, 95, 103, 104, 107–109, 112, 114–117, 119, 121, 123, 126–129, 130, 131, 135, 137–140, 142, 185, 320
representative concentration pathways (RCPs), 11, 32, 38, 45, 46, 51, 61, 66, 68, 90, 103–105, 107, 108, 110, 112, 176, 198, 215, 236, 320
residual error, 231, 242, 285, 287–289
residues, 86, 87, 89
resolution, 49, 51, 52, 264, 265
respiration, 311, 312
response surfaces, 182, 248
rice, 11, 21, 22, 84, 88, 96, 134, 154, 155, 177–179, 205, 248, 300
  rice–wheat cropping system, 116, 134, 135, 142
risk, 7, 69, 132, 133, 135, 227, 298, 304
roots, 86, 154, 314
rural–urban migration, 132
Russia, 193, 206
rust diseases, 306, 318
rye, 205
RZWQM model, 156, 158, 207

SALUS model, 156, 168, 241
sampling, 246, 267, 270–272
SARRA-H model, 156, 158, 207
scaling, 107, 108, 264, 267, 268, 271, 273, 274, 302, 318, 319
scenarios, 3, 10, 28, 31, 45, 49–52, 62, 63, 67–70, 90, 91, 103, 105, 110, 112–115, 117, 118, 123, 127, 131, 137, 139, 140, 142, 148, 161, 166, 176–179, 215, 226, 227, 243, 252, 267, 284, 289, 307
Scotland, 261
SEAMLESS-IF model, 109
Senegal, 125, 133, 193, 206
senescence, 314, 315

sensitivity, 29, 51, 52, 68, 114, 164, 182, 206, 227, 246
sensitivity analysis, 33, 117, 122, 197, 199, 204, 244, 245, 250
sentinel sites, 84, 95
Septoria tritici blotch, 306
shared socio-economic pathways (SSPs), 32, 91, 103–106, 108, 110, 113, 114, 116, 118, 185, 227
slope, 181
smallholder farming systems, 17–20, 22, 133
soils, 37, 80, 82–84, 86–89, 95–97, 112, 120, 135, 147, 148, 150–152, 154, 157, 158, 162, 164, 180, 181, 203, 214, 229, 242, 263, 269, 274, 294, 299, 310, 312
solar radiation, 52, 53, 55, 56, 63, 181
sorghum, 205, 248
South Africa, 7, 92, 93, 125, 133, 206
South Asia, 7, 11, 14, 15, 17–22, 27, 47, 60–62, 67, 70, 118–120, 122, 123, 136, 163, 168
South India, 126, 137
Southeast Asia, 206
southeast South America, 216
southeast US, 248
Southern Africa, 18, 96
sowing date, 82, 85, 86, 89, 93, 94, 269, 273, 312
soybean, 11, 19, 178, 179, 205, 300
soybean rust, 306
SOYGRO model, 315
Spain, 206, 280
spatial scales, 59, 110, 164, 175, 240, 243, 245, 251, 252, 265, 266, 267, 272–274, 301, 302, 305
spatial resolution, 61, 108, 238, 266
Special Report on Emission Scenarios (SRES), 51, 104, 105, 236
SPRiGS model, 207
Sri Lanka, 84, 125, 134, 140, 192, 193, 206
stakeholders, 4, 6, 9, 12, 16–18, 28, 29, 43, 50, 69, 70, 106, 115, 117, 119, 121, 122, 124, 125–131, 137, 139–141, 227, 245
STAMINA project, 241
state variables, 314, 316
statistical models, 41, 238, 283, 286–289, 290, 292, 293
STICS model, 156, 157, 168, 207
storms, 46, 305, 306
stripe rust, 313
Sub-Saharan Africa, 7, 11, 14, 15, 17–20, 27, 47, 61, 62, 67, 70, 118, 120, 122, 123, 136, 163, 168
subsidies, 108, 121, 132, 134, 135
sugarcane, 82, 195, 205
surveys, 85, 88, 152, 158, 160, 164
sustainability, 3, 112, 263
SWAT, Soil and Water Assessment Tool, 109
Sweden, 261
Switzerland, 183

Tanzania, 7, 284, 293
taxes, 108, 132
technology, 31, 36, 37, 39, 41, 42, 81, 91, 95, 97, 108, 110, 120, 132, 134, 135, 164, 167, 242, 312
technology adoption, 34–37, 39, 109
teleconnections, 62
temperature, 7, 8, 11, 18, 53, 55, 19, 29, 52, 56, 58, 62–68, 83, 94, 107, 154, 175, 181, 197, 200–202, 211, 212, 237, 240–242, 248, 250–252, 283–285, 289–293, 297–300, 303–306, 311–314
temporal scales, 263, 265–267, 300, 302–304
Thailand, 192, 206, 214
theory of change, 16
thermal time, 304
threshold, 287
tillage, 150, 181
time periods, 116, 148, 153, 164, 251, 265, 266
TOA-MD, Tradeoff Analysis Model for Multi-dimensional Impact Assessment, 33, 35–37, 41, 42, 80, 81, 85, 90, 104, 109, 115, 126
Togo, 206
tools, 4, 6, 8, 12, 13, 50, 69, 115, 122, 158, 162, 167, 209, 210
topography, 59
trade, 12, 19, 108, 176, 243
training course, 35
transpiration, 314, 317
turgor, 314, 315

UK, 183, 184, 206, 280, 306
UK Department for International Development (DFID), 70
Ukraine, 206

uncertainty, 3, 5, 6, 11, 13, 19, 28, 32, 33, 43, 45, 46, 51, 65, 68, 79, 80, 94, 96, 134, 176, 196, 198, 199, 225, 227, 231, 233–235, 238, 240, 241–245, 248, 250–253, 263, 306
UNFCCC, United Nations Framework Convention on Climate Change, 185
University of Florida, 162
University of Passo Fundo, Brazil, 162
upscaling, 224, 229, 232, 266, 274
urbanization, 297
urea, 152
Uruguay, 280
USA, 46, 59, 147, 168, 183, 184, 192, 206, 211, 243, 261, 279–281, 284, 293
  US Department of Energy (DOE), 70
  USDA, United States Department of Agriculture, 70, 245
use case, 163, 164
user interfaces, 157, 167

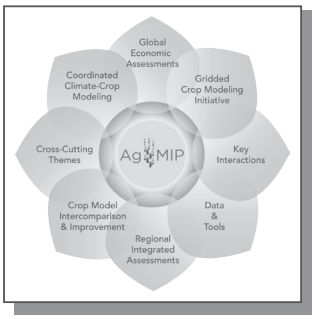
validation, 6, 149, 167, 182, 235
vapor pressure, 52, 55, 63, 181
variability, 52, 57, 67–69, 79, 137, 198, 242, 250, 251, 285, 286, 288, 291, 293, 307
variables, 91, 108, 117, 120, 121, 126, 127, 130, 131, 137–139, 141, 151, 150, 152, 154, 178, 181, 251, 273, 284, 311
varieties, 84, 93, 94, 167, 269, 273
vectors, 309, 310, 319
Verticillium wilt, 314, 315
viruses, 299, 314, 319
visualization, 148
VITE model, 207
vulnerability, 4, 11, 19, 20, 28, 29, 33, 39–42, 103, 107, 133, 135, 184

wage rates, 135
Wageningen UR, 162
WATCH/WFDEI meteorological datasets, 184
water, 18, 56, 83, 86, 88, 109, 112, 120, 134, 135, 154, 179, 180, 211, 243, 273, 312–315, 318
weather, 9, 50, 51, 53, 59, 60, 69, 82, 85, 88–90, 95, 147, 148, 150–152, 158, 161, 162, 164, 175, 180–182, 185, 203, 225, 235, 240, 242, 266, 267, 269, 299, 300, 304, 305, 306, 311, 312, 314, 320
web services, 155, 167, 168, 209
weeds, 33, 315
West Africa, 18, 133, 248
West African Monsoon, 62
wheat, 6, 8, 11, 19, 51, 68, 110, 125, 177–179, 195, 205, 225, 233, 241, 244, 248, 283, 284, 286–288, 291, 292, 294, 300, 304, 306, 313, 318
  wheat rust, 307
  leaf rust (*Puccinia triticina* Eriks.), 318
wind speed, 52, 53, 56, 181
WISE soil database, 148
WMO, World Meteorological Organization, 52, 59
WOFOST model, 156, 168
women scientists, 18
World Climate Research Programme (WCRP), 70
WorldClim climate data, 51, 59, 61, 160
www.agmip.org, 4, 5

xylem, 314

yield, 7, 9, 12, 19–20, 32, 41, 68, 81, 82, 87, 89, 90, 93, 119, 135, 160 177, 184, 202, 209, 210, 225, 241, 242, 248, 271, 272, 285–293, 298, 300, 303, 306, 307, 311, 313, 314, 316, 317, 319, 321

Z-test, 65
Zimbabwe, 125, 132



HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS

The Agricultural Model Intercomparison and Improvement Project Integrated Crop and Economic Assessments, Part 2

Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America

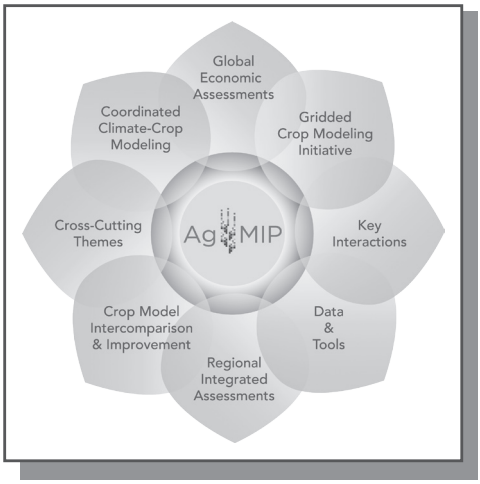
ICP Series on Climate Change Impacts, Adaptation, and Mitigation

Editors-in-Chief: Daniel Hillel and Cynthia Rosenzweig
(Columbia Univ. and Goddard Institute for Space Studies, USA)

Vol. 1: Handbook of Climate Change and Agroecosystems: Impacts, Adaptation, and Mitigation
edited by Daniel Hillel and Cynthia Rosenzweig

Vol. 2: Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications — Joint Publication with the American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America
edited by Daniel Hillel and Cynthia Rosenzweig

Vol. 3: Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments — Joint Publication with the American Society of America, and Soil Science Society of America
(In 2 Parts)
edited by Daniel Hillel and Cynthia Rosenzweig



ICP Series on Climate Change Impacts, Adaptation, and Mitigation – Vol. 3

HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS

The Agricultural Model Intercomparison and Improvement Project
Integrated Crop and Economic Assessments, Part 2

editors

Cynthia Rosenzweig
Daniel Hillel

Columbia University, Center for Climate Systems Research, USA

Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America

American Society of Agronomy | Crop Science Society of America | Soil Science Society of America

ICP

Imperial College Press

Published by

Imperial College Press
57 Shelton Street
Covent Garden
London WC2H 9HE

Distributed by

World Scientific Publishing Co. Pte. Ltd.
5 Toh Tuck Link, Singapore 596224
USA office: 27 Warren Street, Suite 401-402, Hackensack, NJ 07601
UK office: 57 Shelton Street, Covent Garden, London WC2H 9HE

British Library Cataloguing-in-Publication Data
A catalogue record for this book is available from the British Library.

ICP Series on Climate Change Impacts, Adaptation, and Mitigation — Vol. 3
HANDBOOK OF CLIMATE CHANGE AND AGROECOSYSTEMS
The Agricultural Model Intercomparison and Improvement Project (AgMIP)
Integrated Crop and Economic Assessments — Joint Publication with the American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America
(In 2 Parts)

Copyright © 2015 by Imperial College Press

All rights reserved. This book, or parts thereof, may not be reproduced in any form or by any means, electronic or mechanical, including photocopying, recording or any information storage and retrieval system now known or to be invented, without written permission from the Publisher.

For photocopying of material in this volume, please pay a copying fee through the Copyright Clearance Center, Inc., 222 Rosewood Drive, Danvers, MA 01923, USA. In this case permission to photocopy is not required from the publisher.

ISBN 978-1-78326-563-3 (Set)
ISBN 978-1-78326-566-4 (Part 1)
ISBN 978-1-78326-567-1 (Part 2)

Typeset by Stallion Press
Email: enquiries@stallionpress.com

Printed in Singapore

In memory of Dr. Nadine Brisson
(1963–2011)

Dr. Brisson was the leader of the AgMIP Maize Pilot Study and an authority in developing tools to analyze the vulnerability of agricultural systems to climate change. She is remembered around the world for her expertise in crop modeling as well as for her energy, enthusiasm, and commitment to the advancement of agricultural knowledge and understanding for researchers, practitioners, policymakers, and educators. Her brilliant mind and shining spirit are missed by us all.

This page intentionally left blank

Foreword

Though past research has studied temperature and CO_2 effects on crop production, most of it has been done at the disciplinary level, and has not fully utilized on integrated multi-disciplinary approach, with experts in crop and soil sciences, together with agronomists, computer modelers, economists, climatologists, and others working in conjunction. This is the unique research program that AgMIP (the Agricultural Model Intercomparison and Improvement Project) has developed, seeking a voluntary from-the-ground-up approach to advance the field of agriculture as already impacted, and to be further impacted, by climate change.

An imperative task of our time is to develop and implement agricultural practices that can provide the food needed for the anticipated rise in the world's population to around 9 billion in the coming decades, and to do so sustainably without disrupting the remaining natural environment, its ecosystems, and its biota. Much of the debate on meeting future food production goals focuses on expansion of the land area for agriculture and/or intensified crop production on existing agricultural lands. Whereas there is no doubt that concern will focus on the availability of land suitable for agriculture and on improved soil, crop, and water management practices, uncertainty remains concerning the impacts of climate change on crop production. This includes the impacts of rising temperature and atmospheric CO_2 concentration, as well as potential increases in the frequency and intensity of droughts and floods.

The American Society of Agronomy (ASA), Crop Science Society of America (CSSA), and Soil Science Society of America (SSSA) have served as the scientific organizations to host the AgMIP scientists at their 2013 Tampa Annual Meeting, and to be part of this joint publication with Imperial College Press (ICP) on Climate Impacts, Adaptation, and Mitigation. We are especially proud of this volume being dedicated to developing, less-productive regions of Sub-Saharan Africa and South Asia, which are especially affected, and yet have the least information available regarding the portending effects on their major crops.

Related discussion is focused on concepts of "climate-smart agriculture". These concepts are called the "triple-win" approach, consisting of *increasing crop production* with improved agronomic practices, while *adapting to changing climate* and *reducing greenhouse gas emissions*. There is not likely to be a single solution for climate-smart agriculture, as management practices will be regionally determined to accomplish this triple aim, while sustaining soil health and productivity. This is clear from the global and regional assessments presented in this volume. AgMIP is a prime example of developing an integrated approach involving scientists and stakeholders to achieve food security, respond to climate changes, and reduce the scourges of poverty and hunger.

To achieve the triple win within the context of climate change will require much-needed innovative and integrated research such as developed by AgMIP. We congratulate its founders, editors, and contributing scientists on this unique assessment of climate change impacts and the reporting of ongoing regional activities. There is no doubt that these ongoing activities will have a major influence on the management of future agricultural systems under climate change.

Jan W. Hopmans

President, Soil Science Society of America

David B. Mengel

President, Agronomy Society of America

David Baltensperger

President, Crop Science Society of America
Madison, Wisconsin, 2014

Foreword

The *Handbook on Climate Change and Agroecosystems* produced by the scientists of the Agricultural Model Intercomparison and Improvement Project (AgMIP) is a key contribution to a sustainable food and agricultural system in the coming decades. Top agricultural scientists from around the world have taken up the challenge of sustainable agriculture, with the specific focus on integrating agronomic, climatological, biophysical and socio-economic perspectives and processes. Every chapter contributes to addressing the growing food-security challenges facing the world.

The food challenge is profound and complex for four interconnected reasons. First, the rising global population requires rising food production. Second, the pervasive challenges of poor nutrition, ranging from hunger to obesity, demands healthier diets. Third, the adverse environmental effects of farming — including freshwater depletion, loss of biodiversity, pollution, and greenhouse gas emissions — must be reduced. And fourth, the food system is profoundly threatened by the human-induced climate change now underway.

No single study, of course, can examine these profound and interconnected challenges. Indeed the scientific bases for understanding the complex linkages of farming, nutrition, human health, and environmental sustainability, are still being pieced together. This study makes a major, indeed fundamental, contribution to our understanding of the challenges of climate change for the future of agricultural systems around the world.

AgMIP is a unique international collaborative effort to assess the state of global and regional agricultural modeling and specifically to understand the impacts of climate and climate change on the agricultural sector. AgMIP's mission is to improve substantially the characterization of world food security as affected by climate variability and change, and thereby to enhance the capacity of both developing and developed countries to adapt to climate change in future years. AgMIP has grown into a global community of science, with over 700 members from over 40 countries.

The goal of this two-part study is to advance the field by providing detailed information on new simulation techniques and assessments being conducted by

AgMIP. Leading international researchers from across the world have come together to develop improved methods for projecting climate change impacts, adaptation, and mitigation. AgMIP methods and results were cited multiple times in the "Food Security and Food Production Systems" chapter of the IPCC Working Group II Fifth Assessment Report.

A special focus of the Handbook are the AgMIP integrated assessments that were carried out in Sub-Saharan Africa and South Asia from 2011 to 2014 by teams in the region, with major funding from the UK Department for International Development. These regions are among the most vulnerable in the world, and deserve AgMIP's concerted attention.

Over 200 agricultural scientists from around the world, representing a diverse group of developing and developed countries, have collaborated on this AgMIP contribution to the *Handbook on Climate Change and Agroecosystems*. The work is an essential contribution for regional, national, and international agricultural decision-makers who must develop sustainable agricultural systems in a time of accelerating climate change. The scientists who have contributed to this effort merit our deep thanks and appreciation for taking on this challenge of such global significance, and for bringing the best of the world's agronomic, economic, and climatological knowledge to bear in such a useful and comprehensive way.

Jeffrey D. Sachs

Director of the Earth Institute at Columbia University

Special Advisor to UN Secretary General Ban Ki-Moon on the Sustainable Development Goals

Preface

The potential effects of climate change on the food production system are raising concern both globally and regionally. The system is already challenged to deliver sufficient and healthy sustenance to all people, and is certain to be even further challenged as world population grows and price shocks loom. The prospect of climate change intensifies these challenges, raising the risk that more frequent and intense extreme weather events threaten the stability of agricultural production in regions around the globe.

This two-part set is an important contribution to the ongoing Imperial College Press (ICP) Series on Climate Change Impacts, Adaptation, and Mitigation. This series aims to provide the knowledge base necessary for understanding and responding to climate change, in both its current form and future manifestations. In these volumes, leading agricultural researchers have come together to contribute their expertise on actual and potential climate change impacts, adaptation strategies, and mitigation efforts.

This ongoing series is jointly published by The American Society of Agronomy (ASA), Crop Science Society of America (CSSA), and Soil Science Society of America (SSSA), together with ICP. We hope that this fruitful cooperation will continue for many years to come, as it spurs the global effort to define and meet the great food security and climate change challenges of our time.

Cynthia Rosenzweig and Daniel Hillel, Editors

This page intentionally left blank

About the Editors

Cynthia Rosenzweig is a leader in the field of climate change impacts. She is senior research scientist at Columbia University's Center for Climate Systems Research and a professor in the Department of Environmental Science at Barnard College. She is a senior research scientist at the NASA Goddard Institute for Space Studies, where she heads the Climate Impacts Group. She is the co-founder of the Agricultural Model Intercomparison and Improvement Project (AgMIP), a major international collaboration to improve global agricultural modeling, understand climate impacts on the agricultural sector, and enhance adaptation capacity in developing and developed countries. She was a coordinating lead author on observed climate change impacts for the IPCC Working Group II Fourth Assessment. She was named as one of *Nature*'s " Ten People Who Mattered in 2012". A recipient of a Guggenheim Fellowship, she joins impact models with climate models to project future outcomes under altered climate conditions.

Daniel Hillel is a world-renowned environmental scientist and hydrologist. He has worked in over 30 countries across North and South America, Europe, Asia, Africa, and Australia, with a major focus on the Middle East, where he served as a consultant to the governments of Israel, Pakistan, the Sudan, Iran, Egypt, Jordan, and Cyprus. He has worked as advisor to the World Bank and to the United Nations. His innovative techniques in soil and water management have ameliorated the daily lives of the rural citizens of these countries and of countries on all continents. He was awarded the 2012 World Food Prize for his role in conceiving and implementing micro-irrigation, a radically new mode of bringing water to crops in arid and dryland regions. He has published over 300 scientific papers and manuals on agriculture, the environment, climate change, and water-use efficiency, as well as authored or edited 24 books. These have been adopted by many universities as standard teaching and reference textbooks and translated into ten languages.

This page intentionally left blank

Acknowledgments

We especially acknowledge the late Mr. Mark Mandelbaum, the director of publications at ASA/SSSA/CSSA, for his role in bringing this joint project to fruition. He was passionate in disseminating science and technology research to the widest possible readership.

We thank Dr. Zvi Ruder, senior executive editor on behalf of Imperial College Press at World Scientific Publishing, for sharing the wisdom of his lifelong experience in publishing, and we thank Thomas Stottor, editor at Imperial College Press, for his expert and collegial preparation of this book for publication.

We thank Mr. Erik Mencos for his excellent and tireless assistance throughout the entire process of developing the Handbook. We thank Dr. Carolyn Mutter, Dr. Alexander Ruane, Dr. Angela Kong, Dr. Joshua Elliott, Dr. Jeffrey White, Dr. Cesar Izaurralde, Mr. Nicholas Hudson, and Ms. Monica Morales for their chapter reviews. Special acknowledgment is due to Dr. Sonali McDermid for her work on the South Asia and Southern India chapters and to Dr. Roberto Valdivia for his work on economics with the regional research teams. We are very grateful to Ms. Shari Lifson for her preparation of the graphics and final check for the entire volume and to Mr. Roberto Tinella for his assistance with the diagrams and figures.

We are grateful to all of our colleagues from the international agricultural research community who have helped to create AgMIP since its inception and those who are participating in current AgMIP activities. We appreciate especially the guidance provided by the AgMIP Principal Investigators and Steering Group.

Finally, we thank the UK Department for International Development; the United States Department of Agriculture; the CGIAR Research Program on Climate Change, Agriculture and Food Security; the United States Agency for International Development; and the National Aeronautics and Space Administration for their support of AgMIP.

This page intentionally left blank

Contents

Foreword, Jan W. Hopmans, David B. Mengel and David Baltensperger vii

Foreword, Jeffrey D. Sachs ix

Preface xi

About the Editors xiii

Acknowledgments xv

Introduction Introduction to Part 2 xxiii

Section I. Sub-Saharan Africa 1

Chapter 1. Perspectives on Climate Effects on Agriculture: The International Efforts of AgMIP in Sub-Saharan Africa 3

Job Kihara, Dilys S. MacCarthy, Andre Bationo, Saidou Koala, Jonathan Hickman, Jawoo Koo, Charles Vanya, Samuel Adiku, Yacob Beletse, Patricia Masikate, Karuturi P. C. Rao, Carolyn Z. Mutter, Cynthia Rosenzweig, and James W. Jones

Chapter 2. Climate Change Impacts on West African Agriculture: An Integrated Regional Assessment (CIWARA) 25

Samuel G. K. Adiku, Dilys S. MacCarthy, Ibrahima Hathie, Madina Diancoumba, Bright S. Freduah, Joseph Amikuzuno, P. C. Sibiry Traore, Seydou

Traore, Eric Koomson, Alhassane Agali, Jon I. Lizaso, Dougbedji Fatondji, Myriam Adams, Lodoun Tigana, Daouda Z. Diarra, Ousmane N'diaye, and Roberto O. Valdivia

Chapter 3. Impacts of Climate Variability and Change on Agricultural Systems in East Africa 75

Karuturi P.C. Rao, Gummadi Sridhar, Richard M. Mulwa, Mary N. Kilavi, Anthony Esilaba, Ioannis N. Athanasiadis, and Roberto O. Valdivia

Chapter 4. Projected Impacts of Climate Change Scenarios on the Production of Maize in Southern Africa: An Integrated Assessment Case Study of the Bethlehem District, Central Free State, South Africa 125

Yacob G. Beletse, Wiltrud Durand, Charles Nhemachena, Olivier Crespo, Weldemichael A. Tesfuhuney, Matthew R. Jones, Mogos Y. Teweldemedhin, Sunshine M. Gamedze, Pontsho M. Bonolo, Syanda Jonas, Sue Walker, Patrick Gwimbi, Thembeka N. Mpuisang, Davide Cammarano, and Roberto O. Valdivia

Chapter 5. Crop–Livestock Intensification in the Face of Climate Change: Exploring Opportunities to Reduce Risk and Increase Resilience in Southern Africa by Using an Integrated Multi-modeling Approach 159

Patricia Masikati, Sabine Homann-Kee Tui, Katrien Descheemaeker, Olivier Crespo, Sue Walker, Christopher J. Lennard, Lieven Claessens, Arthur C. Gama, Sebastiao Famba, Andre F. van Rooyen, and Roberto O. Valdivia

Section II. South Asia **199**

Chapter 6. Integrated Assessments of the Impacts of Climate Change on Agriculture: An Overview of AgMIP Regional Research in South Asia 201

Sonali P. McDermid, Guntuku Dileepkumar, K. M. Dakshina Murthy, S. Nedumaran, Piara Singh, Chukka Srinivasa, B. Gangwar, N. Subash, Ashfaq Ahmad, Lareef Zubair, and S. P. Nissanka

Chapter 7. Impact of Climate Change on the Rice–Wheat Cropping System of Pakistan 219

Ashfaq Ahmad, Muhammad Ashfaq, Ghulam Rasul, Syed Aftab Wajid, Tasneem Khaliq, Fahd Rasul, Umer Saeed, Muhammad Habib ur Rahman, Jamshad Hussain, Irfan Ahmad Baig, Syed Asif Ali Naqvi, Syed Ahsan Ali Bokhari, Shakeel Ahmad, Wajid Naseem, Gerrit Hoogenboom, and Roberto O. Valdivia

Chapter 8. Integrated Climate Change Assessment through Linking Crop Simulation with Economic Modeling — Results from the Indo-Gangetic Basin 259

Nataraja Subash, Babooji Gangwar, Harbir Singh, Guillermo Baigorria, Alok Kumar Sikka, and Roberto O. Valdivia

Chapter 9. Integrated Assessment of Climate Change Impacts on Maize Farms and Farm Household Incomes in South India: A Case Study from Tamil Nadu 281

Paramasivam Ponnusamy, Geethalakshmi Vellingiri, Raji Reddy Danda, Lakshmanan Arunachalam, Dakshina Murthy, Sunandini Prema, Sreenivas Gade, Sonali P. McDermid, and Roberto O. Valdivia

Chapter 10. Climate Change Impacts on Rice Farming Systems in Northwestern Sri Lanka 315

Lareef Zubair, Sarath P. Nissanka, W. M. W. Weerakoon, Dumindu I. Herath, Asha S. Karunaratne, A. S. M. Prabodha, M. B. Agalawatte, Rasnayaka M. Herath, S. Zeenas Yahiya, B. V. R. Punyawardene, Janan Vishwanathan, Punya Delpitiya, A. Erandika N. Wijekoon, Janaka Gunaratna, Sewwandhi S. K. Chandrasekara, P. Wickramagamage, K. D. N. Weerasinghe, Champa M. Navaratne, Ruchika S. Perera, Asela I. Gunesekara, G. M. Pradeep Kumara, Daniel Wallach, Roberto O. Valdivia, and Sonali P. McDermid

Section III. Other AgMIP Regions 353

Chapter 11. AgMIP Regional Activities in a Global Framework: The Brazil Experience 355

Eduardo D. Assad, Fábio R. Marin, Roberto O. Valdivia, and Cynthia Rosenzweig

Chapter 12. AgMIP Regional Activities in a Global Framework: The China Experience 375

Fulu Tao and Erda Lin

Section IV. Capacity Building and Outreach 391

Chapter 13. AgMIP Training in Multiple Crop Models and Tools 393

Kenneth J. Boote, Cheryl H. Porter, John Hargreaves, Gerrit Hoogenboom, Peter Thorburn, and Carolyn Mutter

Conclusion. Major Findings and Future Activities 411

Cynthia Rosenzweig and Daniel Hillel

Appendix 1. AgMIP Multiple Crop Model Training Program Report 427
Guntuku Dileepkumar, P. Rao, V. Sumanth, Kenneth J. Boote, K. M. Dakshina Murthy, Carolyn Z. Mutter, and Shari Lifson

Appendix 2. AgMIP TOA-MD Economic Modeling Workshop Report 449
John M. Antle, Roberto O. Valdivia, and Shari Lifson

Appendix 3. AgMIP Sub-Saharan Africa Mid-Term Workshop Report 467
Job Kihara, Yacob G. Beletse, Shari Lifson, and Carolyn Z. Mutter

Appendix 4. AgMIP South Asia Mid-Term Workshop Report 505
V. V. S. Kumar, N. Subash, K. M. Dakshina Murthy, Nedumaran, Guntuku Dileepkumar, Shari Lifson, and Carolyn Z. Mutter

Appendix 5. AgMIP Sub-Saharan Africa and South Asia Integrated Assessment Results Workshop Report 553
Job Kihara, Shari Lifson, and Carolyn Z. Mutter

Index 577

This page intentionally left blank

Introduction to Part 2

Part 2 of the two-part set, presents results of the AgMIP regional integrated assessments, providing responses to three core questions: (1) What is the sensitivity of current agricultural production systems to climate change? (2) What is the impact of climate change on future agricultural production systems? (3) What are the benefits of climate change adaptation? Part 2, Section I describes in detail the regions and farming systems investigated in Sub-Saharan Africa, the interactions between the researchers conducting the climate change assessment and their regional stakeholders, the data and methods of study, and their results. Part 2, Section II reports on the methods, data, and results from the AgMIP regional integrated assessments in South Asia. Part 2, Section III highlights AgMIP regional activities in Brazil and China. Part 2 then describes AgMIP capacity-building and outreach activities, including training in multiple crop models and tools. Part 2 ends with a chapter on "Major Findings and Future Activities," providing an overview of the entire two-part set and summarizing key research activities that need to be undertaken to advance knowledge of climate change impacts on agriculture.

Appendices to Part 2 include reports of workshops that were held as part of the UK DFID-sponsored AgMIP Project. Workshops focused on multiple crop model training, TOA-MD economic model training, and Sub-Saharan Africa and South Asia regional integrated assessments.

This page intentionally left blank

Section I

Sub-Saharan Africa

This page intentionally left blank

Chapter 1

Perspectives on Climate Effects on Agriculture: The International Efforts of AgMIP in Sub-Saharan Africa

Job Kihara[1], Dilys S. MacCarthy[2], Andre Bationo[3], Saidou Koala[1], Jonathon Hickman[4], Jawoo Koo[5], Charles Vanya[6], Samuel Adiku[2], Yacob Beletse[7], Patricia Masikate[8], Karuturi P. C. Rao[9], Carolyn Z. Mutter[4], Cynthia Rosenzweig[4], and James W. Jones[10]

[1]*International Center for Tropical Agriculture (CIAT), Nairobi, Kenya*

[2]*University of Ghana, Accra, Ghana*

[3]*AGRA, Accra, Ghana*

[4]*Columbia University, New York, NY, USA*

[5]*International Food Policy Research Institute (IFPRI), Washington, DC, USA*

[6]*Department of Climate Change and Meteorological Services, Blantyre, Malawi*

[7]*Agricultural Research Council, Pretoria, South Africa*

[8]*International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)Bulawayo, Matopos, Zimbabwe*

[9]*ICRISAT, Nairobi, Kenya*

[10]*University of Florida, Gainesville, FL, USA*

Introduction

Agriculture in Sub-Saharan Africa (SSA) is experiencing climate change-related effects that call for integrated regional assessments, yet capacity for these assessments has been low. The Agricultural Model Intercomparison and Improvement Project (AgMIP) is advancing research on integrated regional assessments of climate change that include climate, crop, and economic modeling and analysis. Through AgMIP, regional integrated assessments are increasingly gaining momentum in SSA, and multi-institutional regional research teams (RRTs) centered in East, West, and

Southern Africa are generating new information on climate change impacts and adaptation in selected agricultural systems. The research in Africa is organized into four RRTs and a coordination team. Each of the RRTs in SSA is composed of scientists from the Consultative Group of International Agricultural Research (CGIAR) institutions, National Agriculture Research institutes (NARs), and universities consisting of experts in crop and economic modeling, climate, and information technology. Stakeholder involvement to inform specific agricultural systems to be evaluated, key outputs, and the representative agricultural pathways (RAPs), is undertaken at two levels: regional and national, in order to contribute to decision-making at these levels. Capacity building for integrated assessment (IA) is a key component that is undertaken continuously through interaction with experts in regional and SSA-wide workshops, and through joint creation of tools. Many students and research affiliates have been identified and entrained as part of capacity building in IA. Bi-monthly updates on scholarly publications in climate change in Africa also serve as a vehicle for knowledge-sharing. With 60 scientists already trained and actively engaged in IA and over 80 getting monthly briefs on the latest information on climate change, a climate-informed community of experts is gradually taking shape in SSA. (See Part 2, Appendices 3–5 in this volume for AgMIP Regional Workshop reports.)

Integrated Assessment in SSA

Agriculture in SSA is largely characterized by low inputs and is experiencing climate change-related effects that call for regional integrated assessments. In addition to overall increases in temperature and CO_2 concentrations, regional effects are driven by three key factors, namely tropical convection, monsoons, and the El Niño Southern Oscillation (ENSO). In West Africa, for example, the Sahelian rainfall has strong correlations with the latitudinal position of the Intertropical Convergence Zone (ITCZ; Hastenrath and Polzin, 2011), and there is a unique phenomenon called the monsoon jump (abrupt latitudinal shift of maximum precipitation from the Guinean coast into the Sahel region (Samson and Cook, 2007)). Climate change is likely to affect these drivers in the three major regions in complex and interactive ways.

These three regions, which also differ in terms of their Koppen–Geiger climate classification (Peel *et al.*, 2007), form the key study areas of the AgMIP IA in SSA. Existing information based on modeling of future climate seems to agree on drier western and southern Africa regions and a wetter eastern Africa, although there are intraregional variations (see also Part 2, Chapters 2–5 in this volume). The objective of this chapter is to provide the state of knowledge of modeled climate changes and their effects on crop productivity and household economies, and to present the efforts of AgMIP in furthering IA in SSA.

Climate change in SSA

There is agreement among different general circulation models (GCMs) and associated research that Africa should brace itself for a warmer future world (Waha *et al.*, 2013; see also Part 2, Chapters 2–5 in this volume). Shifts in current zones for agriculture due to climate change have also been suggested, including shifts in the distribution of Köppen–Geiger climate classifications (Hachigonta *et al*., 2013; Läderach *et al.*, 2013; Mahlstein *et al.*, 2013). The pace of the shifts is related to increasing global temperature driven by greenhouse-gas concentrations in the atmosphere. It is expected that temperature changes of up to 2°C would result in climate shifts in 5% of the land and the agricultural impacts of the shifts will vary depending on the amount of land used for agriculture compared to other purposes such as ecosystem (e.g., number of endemic species) or population support (Mahlstein *et al.*, 2013). Some reports, such as that of Zhang and Cai (2013), indicate that climate change may generally favor agriculture in SSA. Others warn that the resulting food-production gains in SSA are likely only in the short run (2030), with losses in the long run (2090; Liu *et al.*, 2013). Most reports however suggest differentiated effects of climate change on agriculture in the regions of SSA (see Hachigonta *et al*., 2013; also Table 1). For example, by 2050, maize yield may increase or decrease by 25% in Malawi and Zimbabwe, depending on the location, and cotton production in Malawi could double (Hachigonta *et al.*, 2013).

The climate change results suggest the need for adaptations if productivity in some of the current SSA production areas is to be sustained, and several researchers have made recommendations. The most comprehensive generalized list of possible adaptation practices in SSA is perhaps by Naab *et al.* (2013) in a previous volume of this series (i.e., Hillel and Rosenzweig, 2013). Some suggested adaptation practices by Naab *et al.* include choice of disease-/drought-resistant crops and their arrangement in sequential cropping systems (Bello *et al.*, 2013; Okonya *et al.*, 2013; Waha *et al.*, 2013), diversity in cropping activities (Muller *et al.*, 2013), improved farm management practices such as use of high levels of nutrients, increased area under irrigation, and high-yielding cultivars (Calzadilla *et al.*, 2013; Delgado *et al.*, 2013; Folberth *et al.*, 2013), and livelihood diversification (Bryan *et al.*, 2013). Since adaptive capacity is dependent on individual resource endowment (Turner and Rao, 2013; Yegbemey *et al.*, 2013), rights of land tenure (Yegbemey *et al.*, 2013), and technological changes (Dietrich *et al.*, 2013), low-income farmers are more vulnerable to the impacts of climate change (Skjeflo, 2013). Thus the complexity and heterogeneity in socio-economic and climatic conditions require adaptation options that consider multiple factors, impacts, vulnerabilities, and potentials. Participation by policymakers and the community is important in the development of adaptation strategies (Bidwel *et al.*, 2013; Vermeulen *et al.*, 2013) and is central to the IA initiatives of AgMIP.

Table 1. Recently published changes in temperature and rainfall predicted for future of SSA.

Temperature	Rainfall	Yield	Model	Focus region	Time-slice	Source
1.5–2	Little change except increasing in extreme northern region	Decreases and increases	CSIRO, MIROC	Zimbabwe	2000–2050	Mugabe *et al.* (2013)
1–1.5	No change	More maize in northern and central regions, less in southern region	CSIRO	Malawi	2000–2050	Saka *et al.* (2013)
1–2	+50 to 400 mm	Increase maize in northern and central regions, decrease in southern region	MIROC5	Malawi	2000–2050	Saka *et al.* (2013)
—	—	Increase	HadCM3, CGCM2, CSIRO2 and PCM	Africa	2030	Liu *et al.* (2013)
—	—	Losses	HadCM3, CGCM2, CSIRO2 and PCM	Africa	2090	Liu *et al.* (2013)
0.5–2.0	+100 to 300 mm	Increase	MIROC5	Kenya	2000–2050	Odera *et al.* (2013)
1–1.5	No change	Increase	CSIRO	Kenya	2000–2050	Odera *et al.* (2013)
1 · 4–4 · 1	+10 to −40%			Ethiopia	2080	Kassie *et al.* (2014)
1–3	>80% of the models variable	—	15 GCMs	Southern Africa	2030–2060	Tadross *et al*. (2011)

AgMIP in SSA

A call for IA in Africa was made by Desanker and Justice (2001) in a special issue of *Climate Research* dedicated to climate change in Africa. However, the challenge for IA for agriculture in SSA is partly related to data-access issues (Cooper *et al.*, 2013) (hence the common use of coarse secondary data; see, e.g., Fischer *et al.*, 2005), and partly to low local technical capacity. Also, while IA requires transdisciplinary approaches, most climate change studies have remained linear, with information flowing from one discipline to another with little cross-disciplinary interaction. AgMIP tries to fill these existing gaps by integrating climate change, agricultural productivity, and socio-economic aspects through coordinated modeling, executed in a looped approach. The key questions that AgMIP is addressing relate to the sensitivity of current agricultural production systems to climate change, the impact of climate change on future agricultural production systems, and the benefits of climate change adaptations. The range of models used in these integrated regional assessments are reported in a comparative review by Dumollard *et al.* (2012), and some of the economic models include crop and climate (as emulator) modules. In AgMIP, the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD) economic model (Antle *et al.*, 2014) is used, taking as input the output of dynamic crop growth models (mainly DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems Simulator), and in some cases AQUACROP and SarraH) and of livestock models such as LivSim (Livestock Simulation Model) and APSFarm (APSIM's Whole-Farm Systems Model). Figure 1 shows the conceptual flow of the IA approach used in AgMIP. The assessments are achieved through coordinated efforts among a multi-disciplinary team composed of climate, crop, and socio-economic scientists (Rosenzweig *et al.*, 2013) who work closely with innovative experts in agricultural-systems information technology.

AgMIP's work on IA in SSA responds to the recommendations of Cooper *et al.* (2013) on the need to (1) improve access to information, (2) build research capacity, and (3) enhance the impact of the research undertaken as the foundation for tackling the climate change challenges in agriculture. The RRTs are the primary groups through which AgMIP is conducting the assessments. The RRTs are multi-country, multi-institutional, multi-disciplinary groups of leading and upcoming scientists in climate, crop, and economic modeling and information technology (IT) in SSA (Table 2). The four RRTs in SSA include impacts of climate variability and change on agricultural systems in East Africa (AgMIP EA), climate change impacts on agricultural systems in West Africa (CIWARA), the Southern Africa Agricultural Model Intercomparison and Improvement Project (SAAMIIP), and Crop–Livestock Intensification in the Face of Climate Change Project (CLIP;

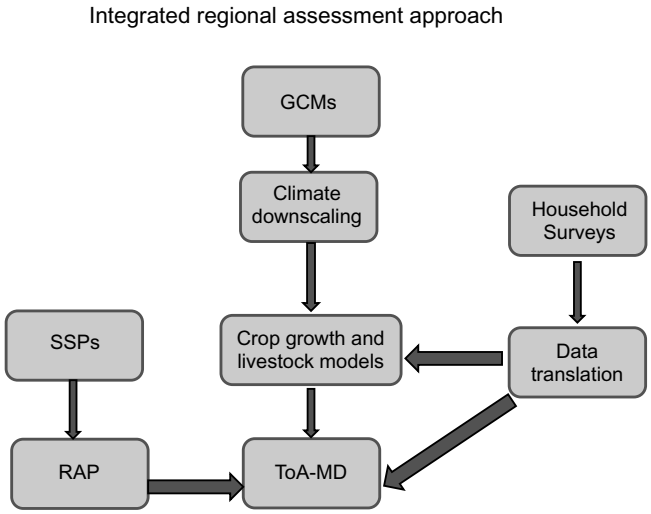


Fig. 1. Integrated regional assessment approach used in AgMIP. GCMs = global climate models, SSPs = shared socio-economic pathways, RAP = representative agricultural pathways.

see Rosenzweig *et al.*, 2013). The RRTs cover the AgMIP regions, countries, and research locations shown in Fig. 2. Each team includes an AgMIP resource person (ARP) who liaises between AgMIP leadership and investigators involved in RRT activities. The multi-disciplinary team of researchers work together not only to understand key disciplinary assumptions (Rosenzweig, 2012), but to define and test assumptions used in the AgMIP integrated modeling approach. A fifth team on knowledge enhancement for climate change referred to as the SSA coordination team provides support for coordinating capacity building and communication amongst the RRTs. The project principal investigators (PIs) and ARPs have formed an SSA leaders committee with scheduled monthly meetings in which management and scientific progress within teams are discussed.

AgMIP has followed a phased approach in order to realize twin goals of capacity building and IA. The first phase was the Fast Track (September 2012 to July 2013), which aimed at getting the basics right and preparing teams to realize the set modeling objectives. This initial phase focused on a few sites where all the modeling activities were implemented at RRT level before teams spread out to conduct research at multiple sites simultaneously (the Homestretch; August 2013–January 2014). In both phases, five general GCMs were used in the three regions, although in some cases up to 20 GCMs have been used, e.g., in East Africa. Baseline (current climate (1980–2010)), mid-century (2040–2070), and end of century (2070–2100) are the three time-slices used. The specific research methods, GCMs, and modeling projections are contained in Part 2, Chapters 2–5 in this volume.

Table 2. Affiliations of AgMIP scientists in SSA.

Institution(s)	Country	Type of institution	Number of scientists
Crop Research Institute in Kumasi	Ghana	NARS	4
University of Ghana	Ghana	University	2
University for Development Studies	Ghana	University	1
SARI	Ghana	NARS	1
Agence Nationale de l'Aviation Civile et de la Meteorologie	Senegal	NARS	1
Agrhymet	Niger	Regional	3
Agricultural Research Corporation	Sudan	NARS	1
Botswana College of Agriculture	Botswana	University	2
French Agricultural Research Centre for International Development (CIRAD)	France	International center	1
CIAT	Kenya	CG center	2
Department of Climate Change and Meteorological Services	Malawi	NARS	1
University of Malawi	Malawi	University	2
Direction Nationale de la Météorologie du Mali	Mali	NARS	1
Mekelle University	Ethiopia	University	
Ethiopia Met Agency,	Ethiopia	NARS	
Ethiopian Institute of Agricultural Research	Ethiopia	NARS	4
Human Sciences Research Council (HSRC)	South Africa	NARS	2
ICRISAT	Kenya, Niger, Zimbabwe	CG center	7
Institut de l'Environnement et de Recherches Agricoles	Burkina Faso	NARS	1
Institute of Rural Development Planning	Tanzania	NARS	1
IPAR	Senegal		1
Kenya Meteorological Department	Kenya	NARS	
University of Nairobi	Kenya	University	
Kenya Agricultural Research Institute	Kenya	NARS	
Uganda Meteorological Department	Uganda	NARS	4
Makerere University	Uganda	University	5
Meteorological Services of Swaziland	Swaziland	NARS	1
National University of Lesotho	Lesotho	University	1
Polytechnic of Namibia	Namibia	University	2
Sokoine University of Agriculture	Tanzania	University	2
Tanzania Meterological Agency	Tanzania	NARS	2
Universidad Eduardo Mondlane	Mozambique	University	1
University of Cape Town	South Africa	University	3
University of Free State	South Africa	University	3
Agricultural Research Council (ARC)	South Africa	NARS	2
South African Sugarcane Research Institute (SASRI)	South Africa	NARS	2

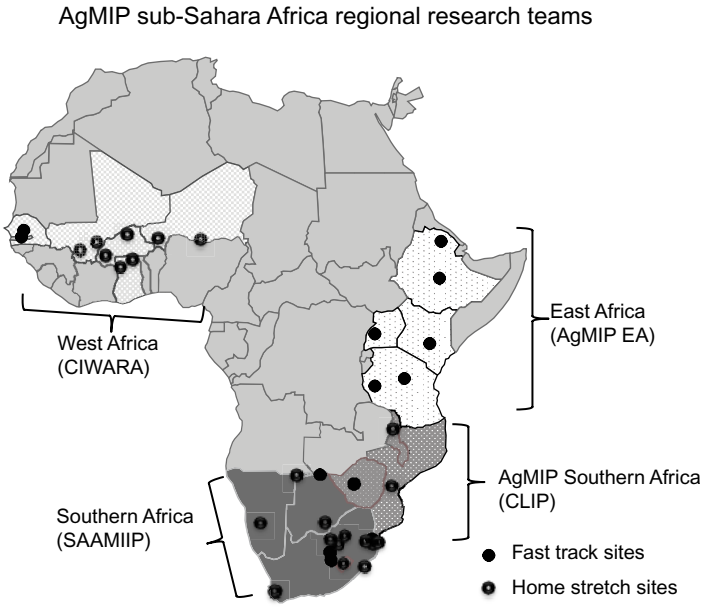


Fig. 2. AgMIP regions, countries, and integrated assessment locations for the AgMIP SSA RRTs.

Identifying and Integrating Stakeholder Concerns

Effective adaptation to climate change and management of risks requires networking between researchers and decision-makers (Bidwel *et al.*, 2013). In SSA, high stakeholder expectations for credible and acceptable IA results are being addressed through an inclusive process where stakeholder concerns are integrated in the assessments. The value of such results was presented by Vermeulen *et al.* (2013), who noted that policymakers in planning for agricultural adaptation would be ready to accept and use "tangible and practical" model outputs on future scenarios of agriculture due to climate change.

Levels of engagement

Stakeholders are engaged at RRT and SSA-wide levels. At the SSA level, stakeholders, mainly technocrats in the agriculture and environment ministries, provide input to the preliminary model simulations of the different teams, and discuss priority food security issues and needs of policymakers that AgMIP can address, including the best ways for AgMIP to disseminate research outputs in the countries. The stakeholders also provide an inventory of key projects in each region/country on climate change so that AgMIP can collaborate and create synergies. Interactions

with stakeholders at the SSA level have provided AgMIP scientists with an opportunity to encourage the inclusion of climate change adaptation plans in government strategy, where these are yet to be included. The engagement forums are also opportunities for countries to learn from those who are ahead in development of the adaptation plans and where scientists are encouraged to move from pilot studies to implementation, and to increase opportunities for integrating science (AgMIP research) and development (appropriate non-governmental organization (NGO) activities).

Key stakeholder concerns

The fusion of farmer concerns, farming systems research, and policymaking brings key challenges for linking science and practice. Making the scientific process useful to decision-making is an outcome that AgMIP researchers and stakeholders strive to achieve in order to create impact through relevant research, better interpretation, visualization, and presentation of results and their communication beyond project partners. This necessitates the AgMIP research teams to engage in discussion with multiple stakeholders to understand context and priorities, addressing questions such as: What are the adaptations currently under consideration? Where do they fall short? What time-scales are most important to the process? What level of detail should key messages contain to be of most use to policymakers? What can stakeholders do to help advance the collaborative AgMIP research methodology? How is climate change information most effectively communicated? How might improved communications be undertaken? What factors limit information-sharing and/or public perception of opportunity through adaptation? What regulatory frameworks are needed to encourage uptake of climate change adaptation strategies (i.e., how can the outcomes of AgMIP's IA activities be implemented)? While the primary concern of stakeholders is the identification and advancement of practices that further versatile and profitable crop management technologies, stakeholder-need discussions tend to fall into science, time-scales, and communication frameworks.

Science

Climate change work should:

(1) Expand in geographical coverage to cover the representative range of soil, climate, and socio-economic situations in SSA as well as temporal variations in the near- and long-term.
(2) Consider drastic/extreme events that may be part of the future climate despite no change in mean rainfall and/or temperature.

(3) Address the question of "what will be the critical point at which the high-potential areas (projected at present not to be affected badly by climate change) become vulnerable?"
(4) Consider changes in and effects of pest/diseases on crop productivity, and address reactions to climate change of crops with different photosynthetic pathways (C3 or C4 plants).
(5) Take into account the broader environmental degradation, including how it is affected by climate change and the feedbacks between the two, e.g., due to extreme events.
(6) Apportion the changes in future productivity to climate change and to degradation of the production base.

Additional work is needed to find out the profitability of the range of options beyond what is tested in AgMIP presently and how much farmers are willing to change to adopt them. This requires participatory action research that involves work with farmers to identify the different constraints and opportunities they would want to seize. Indeed, AgMIP economic analyses show a range of outcomes (losers and gainers) from the various options tested. The analyses could seemingly go an extra step to present alternatives to communities impacted, while also quantifying the benefits of adaptation compared to not taking action. African cropping systems typically involve intercropping of two or more crops—so are more complex than dynamic crop growth model systems at present, which are generally set up to simulate only mono-cropping systems. Researchers need to be able to discuss the extent to which over-simplification impacts adaptation strategies, and what is being done to improve model system simulations to consider even "simple" intercropping systems more appropriately. Scaling of IA results from individual farms to the landscape, regional, and national levels are needed in order to inform policy appropriately.

Time-scales

Although modeling initiatives such as AgMIP have a long-term futuristic focus such as mid-century or late-century time-horizons and their findings directly overlap with needs of development agencies, water resource infrastructure managers, or seed breeders, many farmers want a solution for their immediate/short-term problems. AgMIP is engaging with stakeholders to resolve conflicts in researcher and farmer time-scales considering that both short-term and long-term plans are needed to address climate change. Most countries operate on 5–10-year plans and modelling results of a long-term future (e.g., 50-year time-frames) must be formulated for relevance to the short decision time-frames of farmers and governments. This is important considering that farmers apply heavy discounts to the future (i.e., they invest in short-term benefits).

Communications

Climate change modeling results are associated with high degrees of uncertainty. How this uncertainty in results is communicated to the stakeholders matters. Presenting climate change information to include both positive and negative outlooks is important as opposed to the use of scare tactics about future climate. The messages must be simple and tailored to the target, whether it be farmers or policymakers, most of whom do not speak the language of graphs. The messages can highlight the role of stakeholders and policy in addressing the negative activities contributing to climate change (e.g., activities even external to the agricultural sector). Climate-smart agriculture is becoming more relevant today and, coupled with working agromet services and the evolution of ICT, including bulk and voice-based messaging services, and site-specific production advice in real time is possible.

Refining the stakeholder engagement process

Involvement of stakeholders at all levels is helpful in order to develop comprehensive adaptation packages. In many projects, stakeholders become an add-on to a project designed and implemented without them (see Fig. 3). Usually the stakeholders are invited for a workshop or a project meeting at which they need to advise on communication of results that they are not party to. Project leaders need to identify and sustain the needed engagements at the various project stages. AgMIP RRTs are incorporating feedback from stakeholder into analyses, reports, and publications, and continuously adjusting project plans to accommodate the concerns. Project

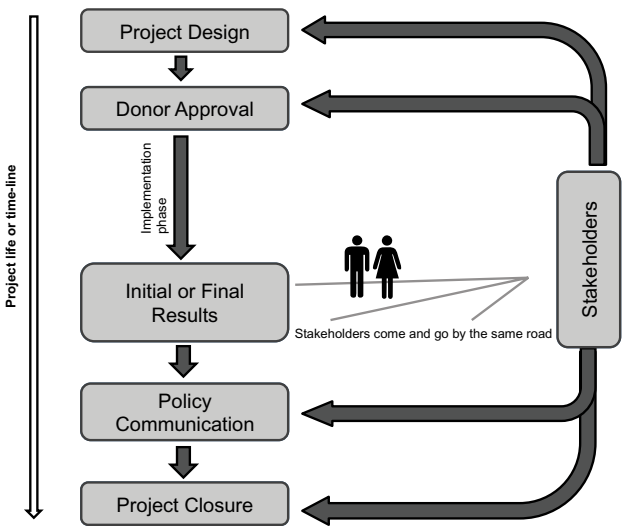


Fig. 3. Stakeholder engagement in project time-line.

self-evaluation is important to assess the evolving needs such as improvements on outreach to farmers and policymakers, and identifying linkages with other related ongoing or emerging initiatives for synergies in addressing the problems in question.

Interactions and engagements in RAP development

The RAP development process is interactive, requiring inputs from stakeholders (Antle, 2011). The definition and considerations of RAPs (including economic and social development storylines, trends in agricultural technology, prices, and costs) are available at www.agmip.org and tradeoffs.oregonstate.edu (see also Rosenzweig *et al.*, 2013). Several RAPs were defined from stakeholder consultations and from the participatory impact pathway analysis. AgMIP Teams are bringing together a wide range of stakeholders in this process including national policymakers, subregional level (such as the Economic Community of West African States (ECOWAS), etc.), and local actors (farmer groups, agricultural NGOs, etc.), with whom extensive discussions are facilitated. Two RAPs were developed for Nioro (Senegal), West Africa, based on four CCAFS scenarios (plausible alternate narratives of the future in terms of socio-economic and political change and the effects of these futures on food security, environments, and livelihoods; see http://ccafs.cgiar.org/). Similarly, 15 stakeholders participated in the development of RAPs for Kenya, building on earlier work through CCAFS. AgMIP is quickly expanding knowledge on RAPs and building the capacity of scientists across SSA and other regions where there is now knowledge of development of the RAPs. Both breadth and depth is needed; AgMIP also endeavors to engage selected stakeholders repeatedly, effectively engaging them in helping to design the looped process of a decision-informed research.

Capacity Building for Climate Change Modeling, Model Intercomparisons, and Improvements

Scientists in SSA require knowledge of the scaling of modeling results. This includes downscaling climate data, economic modeling, and its application in climate impact assessments, and accounting for uncertainties, among others. AgMIP scientists conducting IA are "standing on the shoulders of giants", by continuously interacting and learning from the parents and grandparents of modeling, mainly the model developers. As such, a new generation of modelers with high technical capacity is coming up in SSA. AgMIP is the first major effort to simultaneously build capacity on climate, crop, and economic modeling in SSA. The intensive interactions between model developers and the scientific community in SSA are ensuring in-depth understanding of the working of models and enhanced trouble-shooting capabilities. The capacity building for modeling is further strengthened by training in appropriate presentation

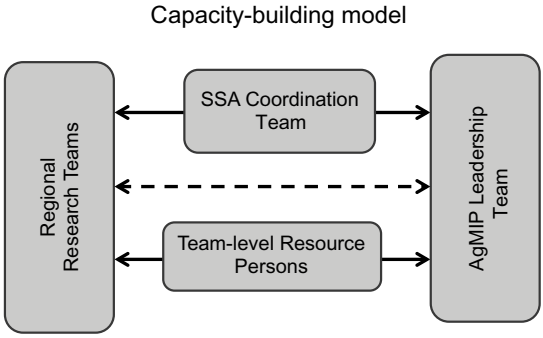


Fig. 4. Identification of capacity-building needs within SSA AgMIP regional teams.

and interpretation of modeling results, and in the communication of the information in relevant forms.

Identification of training needs in AgMIP follows the approach in Fig. 4. Each RRT identifies key areas of capacity-building needed in conjunction with the coordination team. Also, the ARPs within each RRT help to identify needs through routine interactions with project team members. Team-specific training needs, such as individual model parameterization and calibration, are addressed at team level while cross-cutting needs are addressed in SSA-wide forums. The AgMIP approach to capacity-building in modeling is incremental; needs are addressed as they are encountered and it embraces a learning-by-doing approach. Training workshops are preceded by pre-workshop activities, in which teams fulfill a checklist of tasks to prepare so as to maximize learning. See Part 2, Appendices 1 and 2 in this volume for multiple crop model and economic training workshop reports.

Training at RRT level

Multi-pronged training approaches have been adopted in AgMIP within all the RRTs, and several scientists have been trained at least in one key area beyond their prior experience. In addition, cross-disciplinary capacity building has ensured understanding within the integrated research teams. For West Africa, nine scientists have been trained in advanced model calibration at a Multi-Crop Model Training Workshop at ICRISAT, India (see also Part 2, Chapter 13 and Appendix 1 in this volume). Similarly, AgMIP scientists in East Africa trained in the use of crop simulation models (APSIM and DSSAT) and the economic model (TOA-MD; see Part 2, Appendix 2 in this volume), while in Southern Africa, a series of APSIM and LivSim trainings were organized. The trained AgMIP scientists are now generating downscaled climate scenarios, calibrating and validating various crop simulation models in the

target locations, and utilizing the TOA-MD model to project socio-economic outcomes of climate change. Additionally, research assistants and research affiliates are in regular contact with AgMIP scientists for consultation on issues and difficulties they encounter, as and when the need arises. Another capacity-building approach is extended training through MSc programs and full-time hosting of young modelers as visiting research fellows, e.g., the University of Ghana hosting research affiliates. Leading modelers at universities and the Consultative Group of International Agricultural Research (CGIAR) centers also contribute to capacity-building through supervision of university students and staff in other projects.

Training of trainers

Sustainability of capacity-building efforts in Africa is needed, and there have often been failures of previous efforts. Most of the previous efforts have been one-off training workshops with only a few instances of follow-up being sustained (Bationo *et al.*, 2012). In many of these efforts, the trainees were not affiliated with a project in which lessons learnt could be implemented. AgMIP adopted a different approach in which focus is on capacity-building within the project, with scientists immediately implementing the new knowledge. To ensure sustainability, and to develop capacity-building within Africa for Africa, AgMIP has adopted a "training of trainers" approach where promising young crop and economic modelers are involved in the training of their own colleagues. Trainers are distributed across the different SSA regions and RRTs. The trainers have conducted APSIM training in Southern Africa, and DSSAT and APSIM training in West Africa, both in workshops and in specialized one-on-one sessions (see also Part 2, Chapter 13 and Appendix 1 in this volume).

Communication for Impact

SSA level

Information-sharing among scientists and projects in SSA is key to unlocking the potential for IA. As such, the AgMIP SSA coordination team ensures inter-team communication and information-sharing through coordination of monthly virtual meetings of the RRT PIs and ARPs. Also, interteam updates that include key achievements and progress of the individual teams and some synthesis of the most up-to-date knowledge on specific topics (reviewed on a monthly basis) relevant to AgMIP scientists, are shared. The centralized monthly literature review supports teams within SSA with current, topical, and relevant literature for referencing. Through AgMIP's SSA coordination team, a network of climate, crop, and economic modelers has also been established, including AgMIP and non-AgMIP scientists. The monthly

updates are shared with this extended network of modelers with the aim of creating a climate change-aware community of experts in SSA. The monthly briefs are also shared on a blog posted on the AgMIP website (agmip.org; see example below).

AgMIP products are needed for a wide range of audiences at different literacy levels. This is important because access to agricultural information is one of the factors that highly influences farmers' practices (Yegbemey *et al.*, 2013). To realize impact, not only is the right message required in the right form but the right communication channels must be used. In line with this, policy messages or briefs are developed with the help of policymakers. Channels for communicating policy messages include local radio, and AgMIP, through its regional coordination team, is building a network of these channels. The high-level technocrats who participate in AgMIP SSA-wide activities are helping to communicate AgMIP results further.

RRT level

RRTs operate at a regional level and each RRT has developed its own internal and external communication plans. Internal communication is generally through the project PIs. For the two teams in Southern Africa, joint team meetings are held regularly and an oversight committee, composed of members of both teams, ensures complementarity in modeling activities. AgMIP RRTs have designed strategies to ensure open access to information, in which each RRT has websites where its results are communicated and shared, in addition to publications, presentations, and reports. Communication beyond the RRT members includes regional level fora, use of media (TV and radio), and leaflets, among others. The choice of what kind of stakeholders to involve depends on the task at hand, although high-level policymakers or representatives of development institutions are usually preferred.

Data Limitations

The data challenge is acute in SSA. Modeling efforts are often limited by single climate-station datasets or agronomic trials that represent wide geographic areas. For example, only one station's short-term weather dataset was available in Caprivi, Namibia. Even where multiple stations exist, e.g., in Bloem and Thabanchu in South Africa, there are often large data gaps. The problem is especially severe for IA where both crop and socio-economic datasets are needed; often good data are available for one but not the other domain.

Proper archiving of and access to primary datasets by the scientific community is a key recommendation, especially for SSA (Cooper *et al*., 2013), and a key element in AgMIP. At the global level of AgMIP, there is a dedicated IT team that is developing infrastructure for data- and information-sharing for the research community and

Box 1. Climate change impacts on pests and diseases.

The inclusion of pest and diseases in modeling is entering AgMIP's mainstream research. Many crop modeling initiatives do not normally account for effects of pest and diseases, let alone focus on this in the context of climate change. The existing though scanty information indicates that as global warming progresses, latitudinal (and altitudinal) shifts of crop pests are expected, depending on the species (Bebber *et al*., 2013). For example, the tomato red spider mite (*Tetranychus evansi*) is predicted to shift from the current tropical countries in South America and Africa, and temperate regions in North America, the Mediterranean basin and Australia towards northern Europe and some other temperate regions in the Americas by 2080 (Meynard *et al*., 2013).

Africa and other tropical countries will also have to cope with species shifts of viruses and nematodes towards the equator (Bebber *et al*., 2013). In South Africa, and as expected in other zones, differences in ecosystems within a region will have different rates of pests and pathogen development. Van der Waals *et al*. (2013) predicts the cumulative relative development rate (cRDR) of early blight and brown spot in South Africa to increase in the wet winter and wet summer crops of the Sandveld and Eastern Free State, respectively, but to remain unchanged in the dry summer and dry winter crops of the Sandveld and Limpopo, respectively. The cRDR of late blight in all of the cropping systems modeled in this study will decrease, except in the wet winter crop of the Sandveld. This and other approaches encompass uncertainties related to species prevalence, modeling method, and environmental response due to differences within species (as shown by Meynard *et al*., 2013).

How will pest and disease populations affect productivity and economies of future households? This is one of the questions that AgMIP is aiming to answer by capturing climate change effects on pest and disease pressures within dynamic crop growth models.

stakeholders (see also Part 1, Chapter 6 in this volume). To guide usability, AgMIP has defined categories of experimental "sentinel site" field data as silver, gold, or platinum, based on how comprehensive the data is for use in model development, calibration, and validation (see Part 2, Chapter 13 in this volume). In SSA, most of the data are silver or lower categories. This realization is motivating scientists to design new experiments within other funded projects in SSA to ensure improved data collection consistent with modeling requirements. Stakeholders have indicated willingness to mobilize consistent data collection for integrated assessments, e.g., in Mozambique. Data archiving is, as expected, accompanied by metadata that includes information on data collection, quality control, and restrictions on usage.

Access to data required for IA has been a major challenge for the AgMIP RRTs. Extending partnerships to include institutions with needed data, paying for data acquisition, and collecting new data to fill in gaps on agronomic and field management practices were some of the ways to circumvent the data challenge. In some cases, it was not possible to match simulated yields directly with those observed from specific sites but rather comparison of yield distributions of both simulated and observed yields were carried out. Given the usefulness of this approach, there is the need for data collection in subsequent IAs to enable matched-case comparisons.

Multiple-model approaches require IT support and development of data-translation tools. AgMIP tools include R scripts, and visual basic macros (e.g., AgMIP's QuadUI) for data formatting, transformations, and analysis. For details of data translation and other AgMIP IT tools, see also Part 2, Chapter 6 in this volume and agmip.org.

Regional Contrasts

Research results for climate change across SSA are all consistent with a warmer future world, with temperature increases for all emission scenarios, GCMs, and locations (Table 3). Temperatures are projected to increase by 1.5 to 3.5°C in Southern Africa, 0.6 to 3.9°C in East Africa, and 1.7 to 3.2°C in West Africa, according to modeled locations and GCMs used in the AgMIP regional integrated assessments. Rainfall projections, however, are variable, with four of five GCMs showing a wetter East Africa, while West Africa is projected to have reduced rainfall for a majority of the GCMs, although again this varies by the specific subregion. The new results for West Africa show that the northwest will become drier, the northeast will become wetter, while the south will be unchanged (see Part 2, Chapter 2 in this volume).

Table 3. Expected changes in future regional rainfall and temperatures in specific locations in SSA as projected in AgMIP for the mid-century (2040–2069) with selected GCMs and RCP8.5.

	East Africa (AgMIP EA)		Southern Africa (SAAMIIP)		Southern Africa (CLIP)		West Africa (CIWARA)$^{\beta}$	
	Rain	Temp.	Rain	Temp.	Rain	Temp.	Rain	Temp.
CCSM4	+	+	−	+	−	+	−	+
GFDL-ESM2M	+	+	−	+	−	+	+	+
HadGEM2-ES	+	+	+	+	+	+	−	+
MIROC5	−	+	−	+	−	+	0	+
MPI-ESM-MR	+	+	−	+	−	+	−	+

+ = increase, − = decrease, 0 = no change, $^{\beta}$for Nioro site, Senegal.

Besides the subregional variations that are expected as shown earlier, Hastenrath and Polzin (2011) reported variations of observed long-term rainfall in the West African Sahel as prolonged (>10 years) dry and wet regimes that could repeat and influence future climate change. In line with these, Eden *et al.* (2014) have emphasized the need for improved understanding of atmospheric and oceanic drivers of different precipitation regimes as a way of understanding African regional climate changes.

Adaptation options arising from AgMIP

Plausible adaptation options that have arisen from AgMIP scientist–stakeholder discussions include:

(1) The need to consider crop insurance.
(2) Addressing the threats and barriers preventing farmers from moving to the desired state, including soil degradation.
(3) Increases in resilience to pests and diseases.
(4) Low-input costs as well as quality and timely supply of inputs.
(5) Better market development and extension capacity.
(6) Addressing demands for energy that are driving deforestation in SSA.
(7) Enhancing sustainability by including organic resources in modeling scenarios.
(8) Switching to other crops or system diversification.
(9) Non-monetary advancement of sowing dates (appropriate targeting).
(10) Weather forecasting and real-time weather advisories.
(11) Increased use of groundwater for supplemental irrigation, water harvesting, and improving crop and systems water-use efficiency.
(12) Cultivars that optimize water demands at the various crop stages.
(13) Optimized planting density, cultivars tolerant to heat stress, genetically improved long- and short-duration varieties.
(14) Introduction of animal husbandry.

There should be different adaptation strategies for the different categories (operational scale, poverty level, etc.) of farmers, and the strategies should be linked to the livelihoods and show their clear gains. Stakeholder experiences and inputs are needed to help ensure the testing of most appropriate adaptation packages among many options.

Conclusions

AgMIP has a unique approach with good integration between the different disciplines and sectors. It allows for a more holistic approach in assessing climate change impacts and their effects on the income levels of households. AgMIP's need for

good data for integrated modeling within SSA is spurring the setting up of new experiments to generate more high-quality datasets. Further investment in research and development is needed to develop recommendations for the different production systems and environments, and to further capacity building at the national level. The stakeholder involvement process is but one step and in the next phase, AgMIP should engage more with stakeholders for this knowledge to reach the users. Current research is helping identify the most vulnerable farmers so that policymakers can make plans to help those categories, to minimize climate-related risks.

References

Antle, J. M. (2014). Parsimonious multi-dimensional impact assessment, *Am. J. Agric. Econ.*, **93**(5), 1292–1311.

Bationo, A., Tabo, R., Kihara, J., Hoogenboom, G., Traore, P. C. S., Boote, K. J., and Jones, J. W. (2012). "Building capacity for modeling in Africa", in Kihara, J., Fatondji, D., Jones, J. W., Hoogenboom, G., Tabo, R., and Bationo, A. (eds.), *Improving Soil Fertility Recommendations in Africa using the Decision Support System for Agrotechnology Transfer (DSSAT)*, pp. 1–7.

Bebber, D. P., Ramotowski, M. A. T., and Gurr, S. J. (2013). Crop pests and pathogens move polewards in a warming world, *Nat. Clim. Change*, **3**, 985–988.

Bello, M., Salau, E. S., Galadima, O. E., and Ali, I. (2013). Knowledge, Perception and Adaptation Strategies to Climate Change Among Farmers of Central State Nigeria, *Sustain. Agric. Res.*, **2**, 107–117.

Bidwel, D., Dietz, T., and Scavia, D. (2013). Fostering Knowledge networks for climate adaptation, *Nat. Clim. Change*, **3**, 610–611.

Bryan, E., Ringler, E., Okoba, B., Roncoli, C., Silvestri, S., and Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants, *J. Environ. Manage.*, **114**, 26–35.

Calzadilla, A., Zhu, T., Rehdanz, K., Told, R. S. J., and Ringler, C. (2013). Economy-wide impacts of climate change on agriculture in Sub-Saharan Africa, *Ecol. Econ.*, **93**, 150–165.

Cooper, P. J. M., Stern, R. D., Noguer, M., and Gathenya, J. M. (2013). "Climate Change Adaptation Strategies in Sub-Saharan Africa: Foundations for the Future", in Singh, B. R. (ed.), *Climate Change — Realities, Impacts Over Ice Cap, Sea Level and Risks*, InTech Open, Winchester, pp. 327–356.

Delgado, J. A., Nearing, M. A, and Rice, C. W. (2013). Chapter two — Conservation practices for climate change adaptation, *Adv. Agron.*, **121**, 47–115.

Desanker, P. V. and Justice, C. O. (2001). Africa and global climate change: critical issues and suggestions for further research and integrated assessment modeling, *Clim. Res.*, **17**, 93–103.

Dietrich, J. P., Schmitz, C., Lotze-Campen, H., Popp, A., and Müller, C. (2013). Forecasting technological change in agriculture — An endogenous implementation in a global land use model, *Technol. Forecast. Soc.*, **81**, 236–249.

Dumollard, G., Havlík, P., and Herrero, M. (2012). *Climate change, agriculture and food security: a comparative review of global modelling approaches*, CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Working Paper no. 34. Copenhagen, Denmark. Available at: www.ccafs.cgiar.org. Accessed on 17 September 2014.

Eden, J. M., Wildmann, M., and Evans, G. R. (2014). Pacific SST influence on spring precipitation in Addis Ababa, Ethiopia, *Int. J. Clim.*, **34**, 1223–1235.

Fischer, G., Shah, M., Tubiello, F. N., and van Veilhuizen, H. (2005). Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080, *Phil. Trans. Roy. Soc. Biol. Sci.*, **360**, 2067–2083.

Folberth, C., Yanga, H., Gaiser, T., Abbaspour, K. C., and Schulin, R. (2013). Modeling maize yield responses to improvement in nutrient, water and cultivar inputs in sub-Saharan Africa, *Agric. Syst.*, **119**, 22–34.

Hachigonta, S., Nelson, G. C., Thomas, T. S., and Sibanda, L. M. (eds.) (2013). *Southern African Agriculture and Climate Change*, International Food Policy Research Institute, Washington, DC.

Hastenrath S. and Polzin, D. (2011). Long-term variations of circulation in the tropical Atlantic sector and Sahel rainfall, *Int. J. Clim.*, **31**(5), 649–655.

Hillel, D. and Rosenzweig, C. (eds.) (2013). *Handbook of Climate Change and Agro-ecosystems: Global and Regional Aspects and Implications*, Imperial College Press, London, p. 301.

Kassie, B. T., Rötter, R. P., Hengsdijk, H., Asseng, S., Van Ittersum M. K., Kahiluoto, H., and Van Keulen, H. (2014). Climate variability and change in the Central Rift Valley of Ethiopia: challenges for rainfed crop production, *J. Agric. Sci.*, **152**, 58–74.

Läderach, P., Martinez-Valle, A., Schroth, G., and Castro, N. (2013). Predicting the future climatic suitability for cocoa farming of the world's leading producer countries, Ghana and Côte d'Ivoire, *Clim. Change*, **113**, 841–854.

Liu, J., Folberth, C., Yang, H., Röckström, J., Abbaspour, K., and Zehnder, A. J. B. (2013). A Global and Spatially Explicit Assessment of Climate Change Impacts on Crop Production and Consumptive Water Use, *PLoS One*, **8**(2), e57750. D.

Mahlstein, I., Daniel, J. S., and Solomon, S. (2013). Pace of shifts in climate regions increases with global temperature, *Nat. Clim. Change*, **3**, 739–743.

Meynard, C. N., Migeon, A., and Navajas, M. (2013). Uncertainties in Predicting Species Distributions under Climate Change: A Case Study Using Tetranychus evansi (Acari: Tetranychidae), a Widespread Agricultural Pest, *PLoS One*, **8**(6), e66445.

Mugabe, F. T., Thomas, T. S., Hachigonta, S., and Sibanda, L. M. (2013). "Southern African Agriculture and Climate Change: Zimbabwe", in Hachigonta, S., Nelson, G. C., Thomas, T. S., and Sibanda L. M. (eds.), *Southern African Agriculture and Climate Change*, International Food Policy Research Institute, Washington, DC, pp. 289–324.

Muller, M., Sanfo, S., and Laube, W. (2013). "Impact of Changing Seasonal Rainfall Patterns on Rainy-Season Crop Production in the Guinea Savannah of West Africa", prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4–6, 2013.

Naab, J., Bationo, A., Wafula, B. M., Traore, P. S., Zougmore, R., Ouattara, M., Tabo, R., and Vlek, P. L. G. (2013). "Africa perspectives on climate change and agriculture: Impacts, adaptation, and mitigation potential", in Hillel, D. and Rosenzweig, C. (eds.) (2013). *Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications*, Imperial College Press, London, pp. 85–106.

Odera, M. M., Thomas, T. S., Waithaka, M., and Kyotalimye, M. (2013). "East African Agriculture and Climate Change: Kenya", in Waithaka, M., Nelson, G. C., Thomas, T. S., and Kyotalimye, M. (eds.), *East African Agriculture and Climate Change*, International Food Policy Research Institute, Washington, DC.

Okonya, J. S., Syndikus, K., and Kroschel, J. (2013). Farmers' Perception of and Coping Strategies to Climate Change: Evidence From Six Agro-Ecological Zones of Uganda, *J. Agric. Sci.*, **5**, 252–263.

Peel, M. C., Finlayson, B. L., and McMahon, T. A., (2007). Updated world map of the Köppen-Geiger climate classification, *Hydrol. Earth Syst. Sci.*, **11**, 1633–1644.

Rosenzweig, C. (2012). Agricultural futures, *Nat. Clim. Change*, **2**, 567.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013): The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Forest Agric. Meteorol.*, **170**, 166–182.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Mutter, C. Z., Adiku, S., Ahmed, A., Beletse, Y., Gangwar, B., Guntuku, D., Kihara, J., Masikati, P., Paramasivan, P., Rao, K. P. C., and Zubair L. (2012). "The Agricultural Model Intercomparison and Improvement Project (AgMIP): Integrated regional assessments project", in Hillel, D. and Rosenzweig, C. (eds.), *Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications*, Imperial College Press, London, pp. 263–280.

Saka, J. D. K., Sibale, P., Thomas, T. S., Hachigonta, S., and Sibanda, L. M. (2013). "Southern African Agriculture and Climate Change: Malawi", in Hachigonta, S., Nelson, G. C., Thomas, T. S., and Sibanda, L. M. (eds.), *Southern African Agriculture and Climate Change*, International Food Policy Research Institute, Washington, DC, pp. 111–146.

Samson, H. M. and Cook, K. H. (2007). Dynamics of the West African Monsoon Jump, *J. Clim.*, **20**, 5264–5284.

Skjeflo, S. (2013). Measuring household vulnerability to climate change — Why markets matter, *Global Environ. Change*, **23**, 1694–1701.

Tadross, M., Davis, C., Engelbrecht, F., Joubert, A., and van Garderen, E. A. (2014). "Regional scenarios of future climate change over southern Africa", in Davis, C. (ed.), *Climate Risk and Vulnerability: A Handbook for Southern Africa*, Council for Scientific and Industrial Research, Pretoria, South Africa, pp. 28–49.

Turner, N. C. and Rao, K. P. C. (2013). Simulation analysis of factors affecting sorghum yield at selected sites in eastern and southern Africa, with emphasis on increasing temperatures, *Agric. Syst.*, **121**, 53–62.

van der Waals, J. E., Krüger, K., Franke, A. C., Haverkort, A. J., and Steyn, J. M. (2013). Climate Change and Potato Production in Contrasting South African Agro-Ecosystems 3. Effects on Relative Development Rates of Selected Pathogens and Pests, *Potato Res.*, **56**, 67–84.

Vermeulen, S. J., Challinor, A. J., Thornton, P. K., Campbell, B. M., Eriyagama, N., Vervoort, J. M., Kinyangi, J., Jarvis, A., Läderach, P., Ramirez-Villegas, J., Nicklin, K. J., Hawkins, E. D., and Smith, D. R. (2013). Addressing uncertainty in adaptation planning for agriculture, *Proc. Natl. Acad. Sci.*, **110**(21), 8357–8362.

Waha, K., Müller, C., Bondeau, A., Dietrich, J. P., Kurukulasuriya, P., Heinke, J., and Lotze-Campen, H. (2013). Adaptation to climate change through the choice of cropping system and sowing date in sub-Saharan Africa, *Global Environ. Change*, **23**, 130–143.

Yegbemey, R. N., Yabil, J. A., Tovignan, S. D., Gantoli, G., and Kokoye, S. E. H. (2013). Farmers' decisions to adapt to climate change under various property rights: A case study of maize farming in northern Benin (West Africa), *Land Use Policy*, **34**, 168–175.

Zhang, X. and Cai, X. (2013). Climate change impacts on global agricultural water deficit, *Geophys. Res. Lett.*, **40**, 1111–1117.

This page intentionally left blank

Chapter 2

Climate Change Impacts on West African Agriculture: An Integrated Regional Assessment (CIWARA)

Samuel G. K. Adiku[1], Dilys S. MacCarthy[1], Ibrahima Hathie[2], Madina Diancoumba[3], Bright S. Freduah[1], Joseph Amikuzuno[4], P. C. Sibiry Traore[3], Seydou Traore[5], Eric Koomson[1], Alhassane Agali[5], Jon I. Lizaso[6], Dougbedji Fatondji[3], Myriam Adams[7], Lodoun Tigana[8], Daouda Z. Diarra[9], Ousmane N'diaye[10], and Roberto O. Valdivia[11]

[1]*University of Ghana, Accra, Ghana*

[2]*Initiative Prospective Agricole et Rurale, Senegal*

[3]*International Crops Research Institute for the Semi-Arid Tropics, Patancheru, Mali*

[4]*University for Development Studies, Tamale, Ghana*

[5]*Centre Régional AGRHYMET, Niamey, Niger*

[6]*Technical University of Madrid, Madrid, Spain*

[7]*Centre de Coopération Internationale en Recherche Agronomique pour le Développement, Burkina Faso*

[8]*Institut de l'Environnement et de Recherches Agricoles, Ouagadougou, Burkina Faso*

[9]*METEO, Mali*

[10]*Agence Nationale de l'Aviation Civile et de la Météorologie, Senegal*

[11]*Oregon State University, Corvallis, OR, USA*

Introduction

The West African Sub-Saharan region (Fig. 1) is home to some 300 million people, with at least 60% engaged in agricultural activity. Climate change is now recognized as a major constraint to development worldwide. While climate change primarily relates to the future, historical trends give evidence of climate change already occurring. Temperature increases of 1 to 1.5°C have been observed over the last 30 years

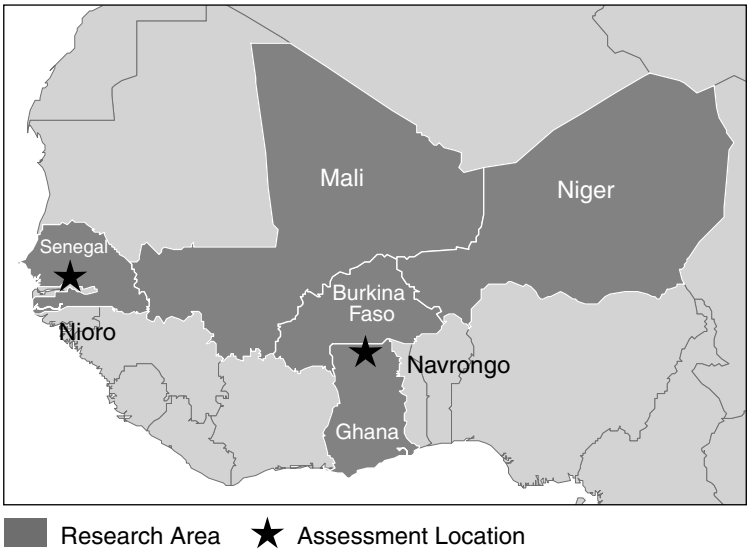


Fig. 1. Map of West Africa indicating the countries and sites included in the study.

in West Africa (EPA Ghana, 2001; IPCC, 2007) and there are projections of further warming of the West African region in the foreseeable future (2040–2069; Fig. 2a). The impact of climate change on West African rainfall is less clear. The analysis of historical data over the last 30 years shows that, whereas some zones experienced increased rainfall by as much as 20% to 40%, other locations experienced a decline in annual rainfall by about 15%. Future projections suggest a drier western Sahel (e.g., Senegal) but a wetter eastern Sahel (e.g., Mali, Niger; Fig. 2b). The southern locations of West Africa (e.g., Ghana) are projected to experience no change or slight increases in annual rainfall (Hulme *et al.*, 2001).

Irrespective of whether these zones will be dryer or not, there is historical evidence of shifts in rainfall patterns with extreme events (i.e., droughts and floods) becoming more frequent (Adiku and Stone, 1995) and it is probable that this trend may persist into the future.

Climate change impacts

The increased warming and shifts in rainfall patterns associated with climate change would adversely affect West African agriculture, which contributes between 40% and 60% of gross domestic product (GDP). Agriculture in West Africa is dominated by a large number of smallholder farmers, who cultivate a range of cereals (e.g., millet, maize, and sorghum) and legumes (e.g., peanut, cowpea, and soya).

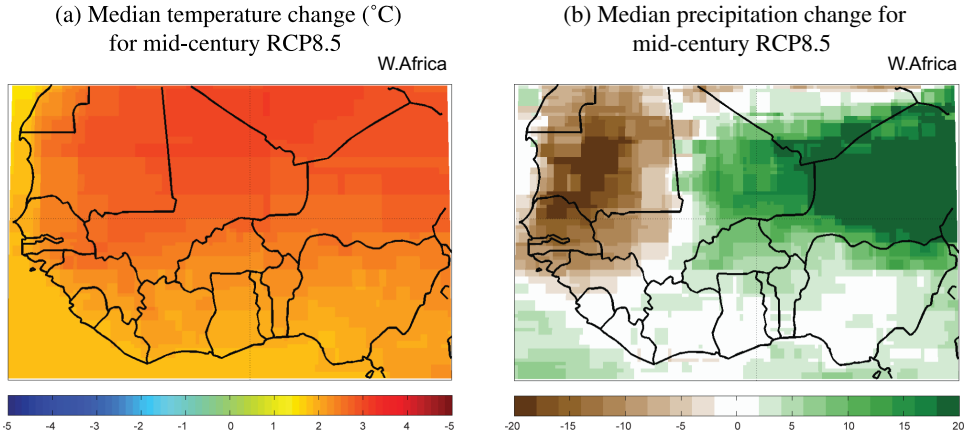


Fig. 2. Projected changes in West Africa (median from 20 GCMs) of (a) median temperature change (°C) for mid-century RCP8.5 and (b) median precipitation change (%) for mid-century RCP8.5 in the study sites, Nioro, Senegal, and Navrongo, Ghana.

Crop farmers in West Africa rely largely on the soil's inherent fertilityfor production. The removal of crop residue after grain harvest for feed, fuel, and other purposes further impoverishes the soil, as this residue is the main source of soil organic matter (SOM). Studies by Adiku *et al.* (2009) showed that the regular removal of residue from an initially long-term fallowed cropland reduced the SOM by over 50% within a period of four years. Many previous studies such as that of Brams (1971) also observed a 50% decrease of organic matter within the top 0.2 m in the ferallitic soil of Sierra Leone after five years of land clearing and continuous cultivation. Crop and range productivity is thus generally very low in the region, often lower than 1500 kg/ha in the case of cereals and 1000 kg/ha for legumes.

Studies indicate that future climate change will adversely affect development and living standards in West Africa because of a number of independent factors: (1) high dependence of people and their livelihoods on natural resources, livestock, and cropping agriculture; (2) high rate of degradation of these natural resources, which renders them less resilient; (3) extreme poverty with *per capita* earnings as low as $750/yr in Senegal (Khouma *et al*., 2013) and $1,000 in Ghana (Nutsukpo *et al*., 2013); and (4) lack of social intervention schemes (e.g., agricultural insurance), which makes it difficult to respond to increased incidence of climate extremes.

The combination of these factors and the possible changes in future rainfall lead some researchers to project future declines in crop productivity in the region. For example, Nutsukpo *et al.* (2013) projected a future decline in maize yields in Ghana by the year 2050 of 25% below the 2005 base year. Even though the basis for such projections is not entirely clear (especially as they are based on single historical and future-year simulations without capturing the heterogeneity in

the socio-economic dynamics of the farming community and uncertainties of the projection methodologies), they are often used as the basis for proposing adaptation strategies to minimize climate change impacts. However, with limited quantitative aspects and no defined framework within which to operationalize these interventions, their value for policy formulation and implementation is limited.

Given that agricultural production entails the interplay of socio-economic factors (e.g., households), biophysical factors (e.g., soil and climate), and management decisions (e.g., agronomic practices) as well as policy decisions (e.g., subsidies), an integrative assessment approach would be required for improved decision-making. This chapter demonstrates the AgMIP methodology in analyzing the impact of climate change on West African agriculture. The research questions posed relate to (1) the sensitivity of current agricultural production systems to climate change, (2) the impact of climate change on future agricultural production systems; and (3) the potential benefits of climate change adaptations.

Farming System Investigated

Settings and locations

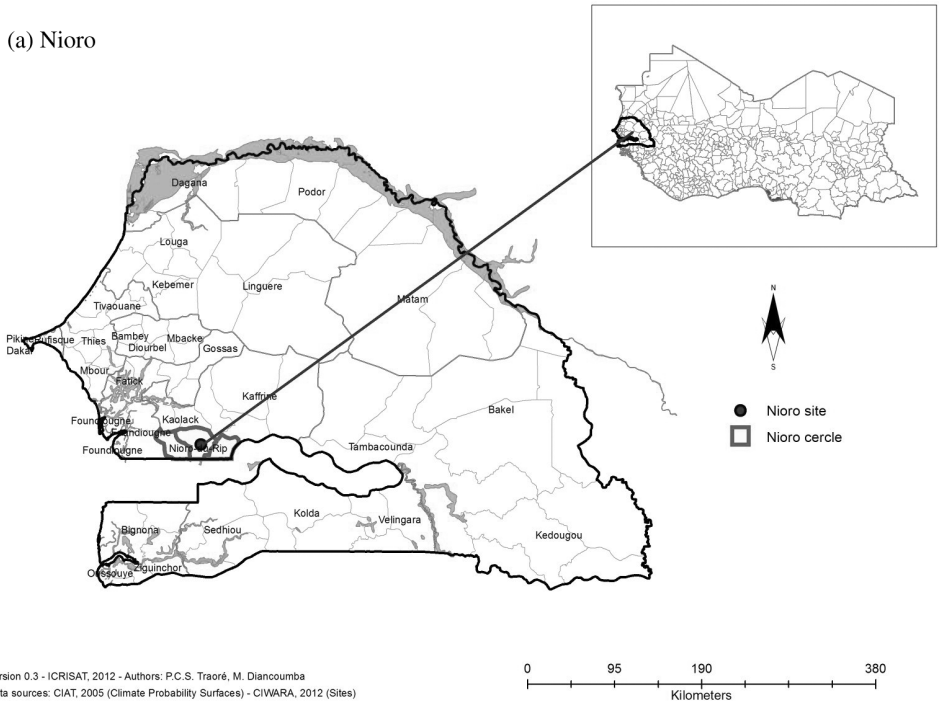
In this study, two sites are included to provide a comparative perspective. Figure 3 shows the two sites, Nioro in Senegal and Navrongo in Ghana. Nioro is located at latitude 13.7°N, longitude 34.4°W, and an elevation of 30 m. Navrongo is located at latitude 10.89°N, longitude -1.09°W, and an elevation of about 197 m above sea level. Economic analysis, however, was not done for the Navrongo site in this study.

Climate and soil data

Weather data for the survey year (2007), as well as the long-term baseline (1980–2010) climate records (e.g., solar radiation, maximum and minimum air temperatures, precipitation, wind speed, humidity, and vapor pressure) were obtained for Nioro du Rip City from the Senegal National Weather Agency. Additionally, rainfall data for the village locations were derived from the WorldClim database. For future projections (2040–2069), five general circulation models (GCMs) (namely CCSM4, GFDL-ESM2M, Had GEM2-ES, MIROC5, and MPI-ESM-MR (Rosenzweig *et al.*, 2013)) were used for the RCP 8.5 scenario, which assumes an elevated CO_2 concentration of 571 ppm compared with the current 390 ppm.

Future climate scenarios were produced using the delta method (see Chapter 3 of Part 1 of this volume), which involves adjusting daily historical observations to match mean monthly climate changes in temperature and percentage changes in precipitation as determined by GCM simulations over the 1980–2009 baseline

(a) Nioro



(b) Navrongo

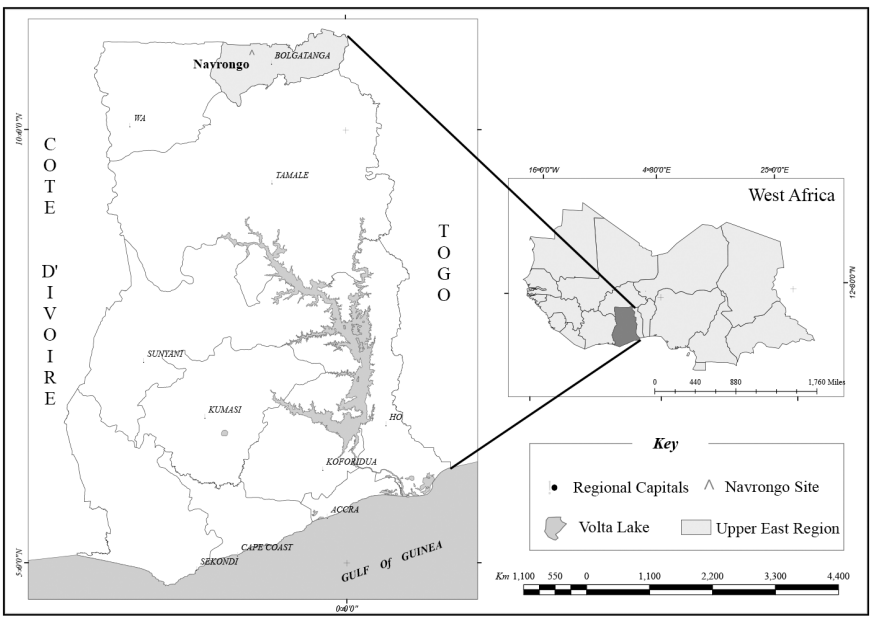


Fig. 3. Study sites: (a) Nioro, Senegal; (b) Navrongo, Ghana.

period. Solar radiation data and short gaps in temperature data were filled using the AgMERRA data set (Ruane *et al*., 2014). In the case of Navrongo (2012), baseline climate data were obtained from the Ghana Meteorological Agency in Accra. Future projections were obtained using the same procedure as for Nioro. The soils in the Nioro basin are fairly deep, reaching depths of 100 cm (Table 1a). Four major soil types can be discerned in the basin, one of which is sandy with a clay content of less than 20%. The others have appreciable clay content, reaching 45% at greater depth. Unlike Nioro, the soils of Navrongo, which can be classified as Endoeutric-stagnic Plinthosol and Eutric Gleyic Regosols, are typically shallow, containing high proportions of coarse fractions (Table 1b).

Farming system

Agriculture in West Africa is dominated by a large number of smallholder farmers (with farms ranging from 1 to 2 ha), cultivating a range of cereals (millet, maize, and sorghum) and legumes (peanut, cowpea, and beans). Livestock plays a significant role in the functioning of the overall system through its dependence on crop residues

Table 1a. Soils of Nioro du Rip Basin and Navrongo (West Africa).

	L	LL	DUL	SAT	BD	OC	CLY	SIL	CF	pH	CEC
Soil ID	Cm	cm^3/cm^3	cm^3/cm^3	cm^3/cm^3	g/cm^3	%	%	%	%		cmol/kg
ITSN	20	0.1	0.162	0.38	1.46	0.538	14	8	10	5.6	4.9
840067	40	0.12	0.188	0.373	1.48	0.64	18	9	10	5.1	5
	60	0.133	0.195	0.358	1.53	0.424	22	7	10	5.1	6
	80	0.143	0.2	0.375	1.48	0.28	25	5	10	5.1	5
	100	0.155	0.218	0.398	1.51	0.28	25	5	2	5.1	5
ITSN	20	0.113	0.206	0.331	1.34	0.8	19	27	28	5.1	4
840080	40	0.089	0.165	0.278	1.46	0.715	18	27	34	5	4
	60	0.088	0.16	0.301	1.48	0.22	18	26	28	5.3	3.8
	80	0.08	0.151	0.293	1.51	0.2	16	26	28	5.4	3.5
	100	0.053	0.101	0.298	1.54	0.154	15	26	50	5.4	3
ITSN	20	0.114	0.193	0.443	1.4	0.648	14	12	0	6.1	3
840042	40	0.167	0.253	0.452	1.38	0.42	26	14	0	5.1	4
	60	0.218	0.306	0.445	1.4	0.437	36	12	0	5	4
	80	0.261	0.35	0.42	1.47	0.362	45	11	0	5	4
	100	0.26	0.348	0.456	1.37	0.32	45	11	0	5	4
ITSN	20	0.072	0.147	0.396	1.42	0.146	10	21	10	6.4	3
840056	40	0.12	0.197	0.376	1.48	0.26	20	18	10	6.4	2
	60	0.13	0.206	0.359	1.53	0.31	22	16	10	6.4	2
	80	0.13	0.206	0.375	1.48	0.31	22	16	10	6.4	2
	100	0.167	0.248	0.352	1.5	0.295	32	18	14	5.4	3

Table 1b. Soils of Navrongo, Ghana.

	L	LL	DUL	SAT	BD	OC	CLY	SIL	CF	pH	CEC
Soil ID	Cm	cm^3/cm^3	cm^3/cm^3	cm^3/cm^3	g/cm^3	%	%	%	%		cmol/kg
	15	0.15	0.203	0.352	1.56	0.39	12	16	71		
	30	0.11	0.209	0.321	1.58	0.36	17	21	62		
	50	0.11	0.205	0.32	1.56	0.32	12	16	71		
	15	0.12	0.203	0.352	1.56	0.39	12	16	71		
	30	0.09	0.209	0.321	1.58	0.36	17	21	62		
	50	0.11	0.205	0.32	1.56	0.32	12	16	71		
	15	0.1	0.203	0.352	1.56	0.58	12	16	71		
	30	0.09	0.209	0.321	1.58	0.56	17	21	62		
	50	0.11	0.205	0.32	1.56	0.45	12	16	71		

CLY=clay, SIL=silt, CF=coarse fraction, CEC=cation exchange capacity, LL=wilting point, DUL=field capacity

as feed, and provision of manure to the cropping system (Fig. 4). Agriculture is mainly rainfed. The use of manure for cereal farming is limited to the homestead. Agriculture in the study area is dominated by millet and peanuts grown in annual rotation. Maize is also cultivated, but to a lesser extent. Fallow durations tend to disappear under population pressure. Very few farmers apply mineral fertilizers. As a result, average yields of cereals and peanut are low.

Stakeholder Interactions, Meetings, and Representative Agricultural Pathways

The process of developing representative agricultural pathways (RAPs) began with consultations with appropriate personnel in government establishments that work in the sector responsible for agriculture. Additionally, non-governmental organizations (NGOs) working in the area of agriculture and climate change and scientists working in the subject area were engaged on the subject. The meetings were in the form of informal conversations, formal presentations of CIWARA's work at workshops to solicit informed discussions. These interactions helped in arriving at the RAPs that were developed. Additionally, a number of adaptation measures were discussed but only one of the adaptations was simulated in this study.

Representative Agricultural Pathways

An integrative assessment of climate change impacts on the future of agriculture in West Africa must of necessity consider the development policies and the

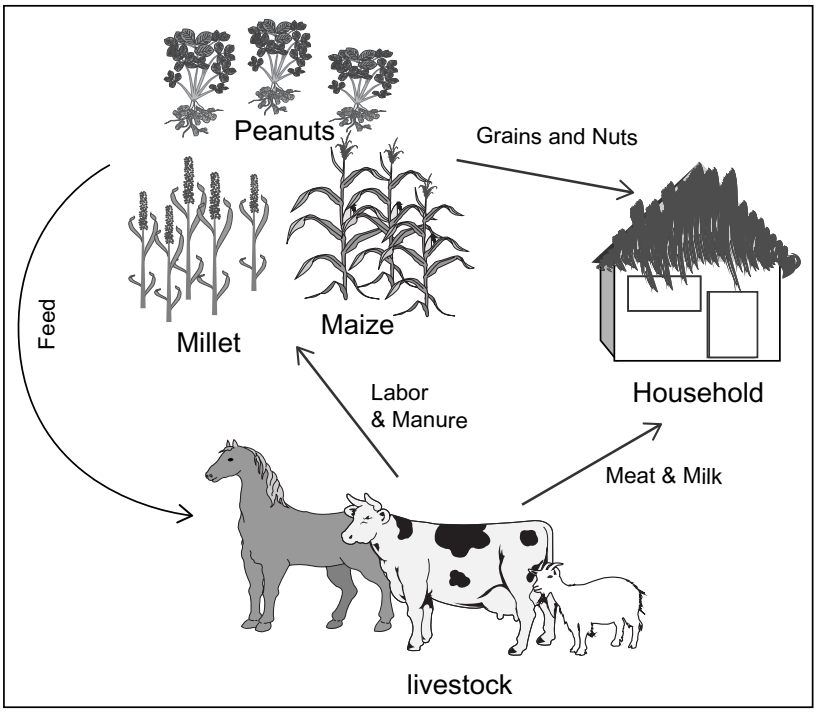


Fig. 4. Farming systems diagram for Nioro and Navrongo.

socio-economic pathways that are currently in place and projected for the future. By following a number of stakeholder interactions and surveys by the research program on Climate Change, Agriculture, and Food Security (CCAFS), and AgMIP, a two-pronged development pathway can be described.

First, short-term RAPs foresee the continual dominance of state actors in the agricultural development agenda with the view of bringing in fast short-term gains in food security outcomes for the population. Within this short term, several changes are expected in the agricultural sector. On the biophysical front, small and fast-growing animal (e.g., poultry) production would increase as there is pressure to meet the protein demands of a rapidly increasing urban population. The use of high-yielding crop varieties and application of agrochemicals would also increase. On the policy front, there would be a drive to facilitate agricultural extension and agro-processing. However, infrastructure improvement would concentrate in the urban centers. On the socio-economic front, rural household sizes would decrease due to the high rural-to-urban migration, increased efforts to enhance women's literacy, and the quest to improve living standards by rural communities. As a result, the main interventions are likely to include state support for the agricultural service sector,

fertilizer subsidies, and preference for importing cheaper food over an apparently more expensive domestic production.

Second, long-term RAPs for many West African countries foresee the situation whereby the role of the private sector would become more relevant in agriculture. Organized civil society demand for higher food quality must also be factored in. This transformative path could lead to an emerging agricultural powerhouse in West Africa with reliance on strong private agrobusinesses that deliver healthy food choices to meet consumer preferences, improved climate information delivery services to farmers, improved soil management, and development of seed technologies that would address climate change effects. On this study, adaptation strategies examined are limited to the performance of new crop varieties that can withstand projected temperature increases and increased rainfall variability under climate change.

Data and Methods of Study

Climate

Observed trends in temperature and precipitation

In Nioro, the minimum temperature during the crop growing season (May to October) ranged between 13.1 and 20.5°C, with a mean of 18.2°C over the baseline period. As for maximum temperature, this ranged from 41.8 to 46.3°C with a mean of 43.8°C. Annual rainfall ranged between 418 and 1035 mm with a mean of 725 mm over the 30-year period (1980–2009). The observed trends show a sharp increase in maximum temperature, and slight increases in annual rainfall and minimum temperatures (Fig. 5).

In the case of Navrongo, minimum temperature ranged between 15.6 and 20.6°C, with an average of 19.2°C. As for maximum temperature, it ranged from 38.0 and 42.8°C, with an average of 40.4°C. Annual rainfall amounts ranged between 688 and 1365 mm, with an average of 969 mm over the 30-year period. The observed trends are not significant for maximum temperature and annual rainfall, but minimum temperatures show some slight increase.

Climate projections and significance tests for delta method changes

A significance test was done for the projected change in the total rainfall and the average maximum temperature for the growing period (from May to October at all sites). The (Δs) criterion, which serves as the significance threshold, is equal to the standard deviation for the 30-year baseline period (1981–2010) multiplied by a factor of 0.36 (see Part 1, Chapter 3 in this volume). For maximum temperature, this corresponded to 0.14°C at the two sites, a threshold which is largely expected to be

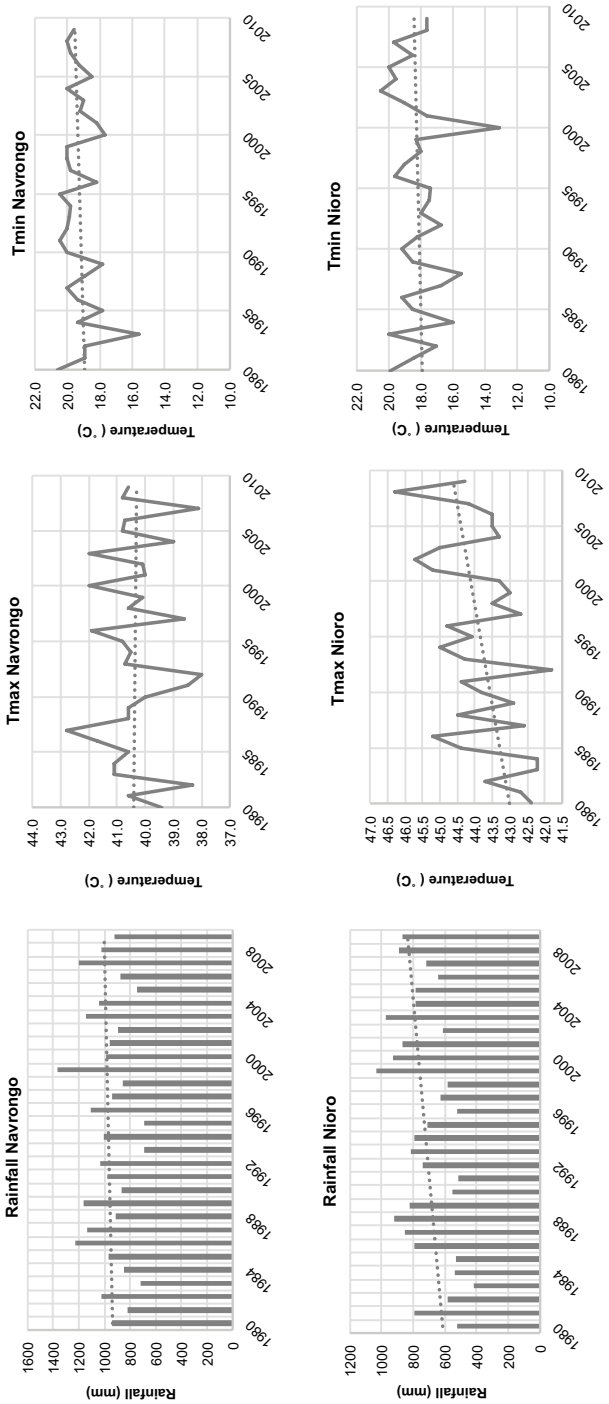
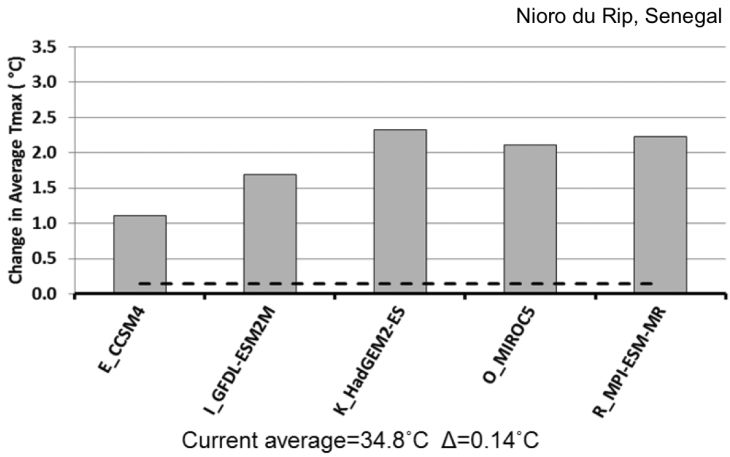


Fig. 5. Historical (1980–2009) crop growing season (May–October): cumulative rainfall amounts, absolute minimum, and absolute maximum temperatures for Nioro, Senegal, and Navrongo, Ghana.

(a) Change in average maximum temperature



(b) Change in average maximum temperature

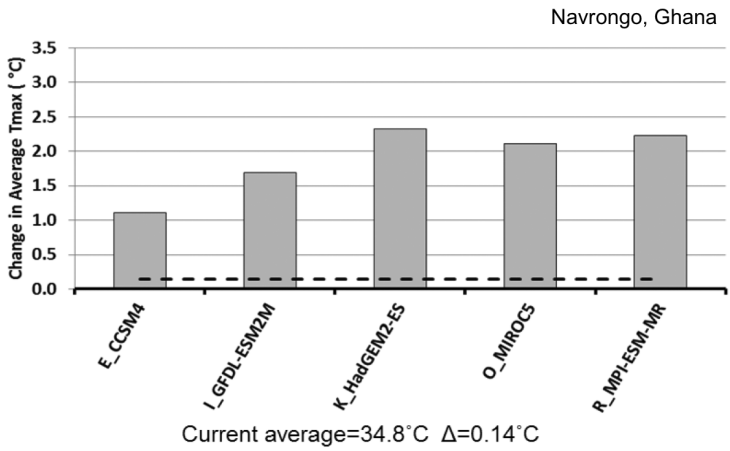


Fig. 6a. Comparison of projected maximum temperature with that of baseline climate in the growing season (May to October) for Nioro, Senegal, and Navrongo, Ghana. Dashed lines represent the (Δs) threshold for statistically significant changes relatively to the 30-year baseline period (1981–2010).

exceeded everywhere and according to all five GCMs tested. Indeed, the expected increases in temperature range from 1.7 to 2.3°C in Nioro, and from 1.8 to 2.8°C in Navrongo (Fig. 6a). The greatest warming is projected by HadGEM2-ES and the least warming is projected by CCSM8 at both sites.

Regarding cumulative rainfall, the expected changes are not uniform across the GCMs and the sites. The value of the (Δs) criteria is equal to 8.8% in Nioro and 6.8% in Navrongo. Both sites are likely to experience both positive and negative changes, depending on the GCM relative to the threshold. In the case of Nioro, four

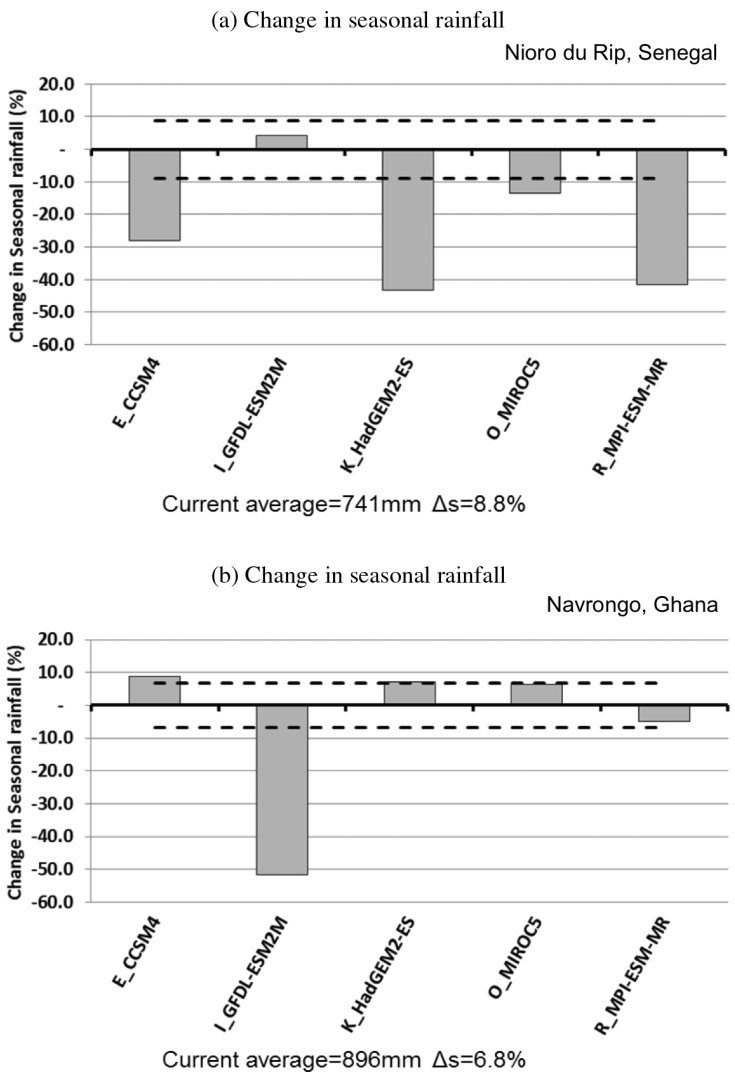


Fig. 6b. Projected changes in growing season (May to October): cumulative rainfall at Nioro, Senegal and Navrongo, Ghana. Dashed lines represent the Δs threshold for statistically significant changes relative to the 30-year baseline period (1981–2010).

out of the five GCMs predict a decreased seasonal rainfall by 13.5 to 43.3%. Only GFDL-ESM2M predicts a slight, not significant increase in seasonal rainfall at this site (Fig. 6b). As for Navrongo, while GFDL-ESM2M predicts a dramatic decrease (−51.7%) in seasonal rainfall, the other GCMs predict barely significant but positive changes (Fig. 6b). The projected changes in average monthly mean temperature and rainfall, as well as the scatter of the 20 CMIP5 GCM projected values relatively to the baseline period (1981–2010) for the two locations are given in Fig. 7a and

Fig. 7b. From these graphs, it is evident that while all GCMs agree on a temperature increase, there are differences in the magnitude and direction of the changes in precipitation. Indeed, while a median decrease in precipitation is foreseen during the rainiest months in Nioro, no change is expected in the early part (April, May, June, July) of the season, but some increases are expected in the latter part (August, September and October) in Navrongo.

Crops

Crop model calibration (*DSSAT and APSIM*)

Two crop models were used in this study, namely (1) Decision Support System for Agrotechnology Transfer (DSSAT v. 4.5) (Jones *et al.*, 2003), and (2) Agricultural Production Systems Simulator (APSIM v. 7.5) (Keating *et al.*, 2003). The DSSAT model was previously used in simulation studies in Ghana (Adiku *et al.*, 2007; MacCarthy *et al.*, 2010; MacCarthy *et al.*, 2013) and in the Sahel (Traore *et al.*, 2007). The APSIM model was also used in previous studies in West Africa (Akponikpe *et al.*, 2010; MacCarthy *et al.*, 2009). However, the models were re-calibrated as shown in Table 2 for the crop varieties grown at Nioro, Senegal, and Navrongo, Ghana. For Nioro, the selected millet variety was *CIVT* and the calibration dataset was from Akponikpe (2008) and Akponikpe *et al.* (2010). For maize, *TZEY-SRBC5* was selected for Nioro and the calibration data were from Dzotsi *et al.* (2003). In the case of Navrongo, the maize variety was *Obatanpa* with calibration from Dzotsi *et al.* (2010). For peanut, the *Chinese* variety was selected for all sites with Naab *et al*. (2004) as the calibration dataset. In the current study, the DSSAT and APSIM models were used to simulate all three crops (millet, maize, and peanut).

Additional model parameterization and validation

Following the calibration of the crop models, they were validated for 226 farms at Nioro and 250 at Navrongo, with derived model input data from the household survey information. The parameterization of the models using household data brought with it many challenges. First, given the frequently low crop yields reported in the survey, it was necessary to re-examine the soil data, which were based on the National Soil Survey Manual rather than actual soil surveys. In situations where the reported soil organic carbon (SOC) was high, SOC values were re-adjusted so that their contribution to soil fertility was reduced by increasing the proportion of the stable fraction, which is the inert carbon. A previous study by Bostick *et al.* (2006) lends support to this approach. For DSSAT simulations of millet and peanut, the stable carbon proportion was gradually adjusted from 0.7 to 1 from the top to the bottom of the soil profile. In APSIM, the stable carbon fraction was similarly varied from

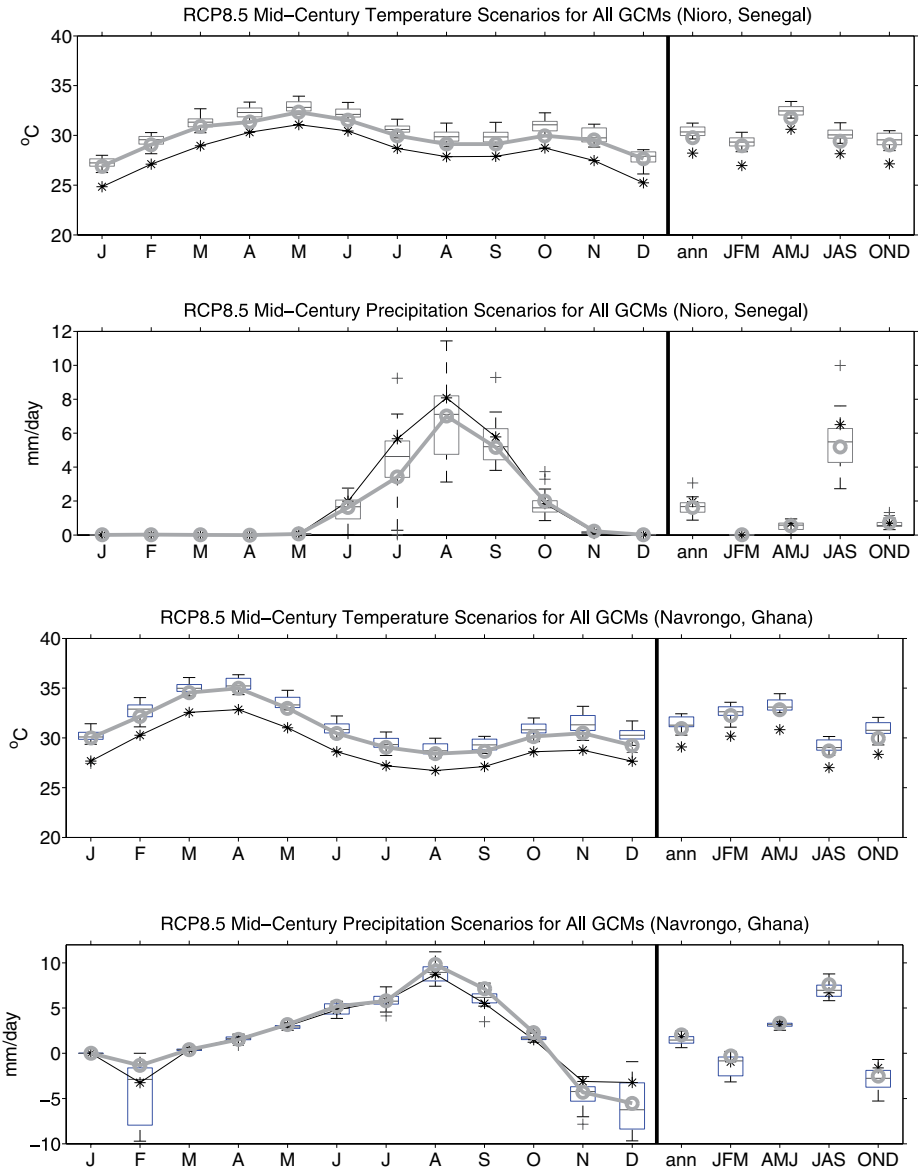


Fig. 7a. Projected changes in average monthly mean temperature and rainfall at Nioro, Senegal, and Navrongo, Ghana. The black line represents the average values for the 30-year baseline period (1981–2010) and the gray line represents the median of the projected values by 20 CMIP5 GCMs.

0.8 to 1 from the top to the bottom of the soil profile. In the case of maize, the soil fertility parameter factor (SLPF) in DSSAT was used to adjust soil productivity.

Second, the household survey for the base years provided information for sowing windows only, rather than actual sowing dates. For realistic simulation at the study

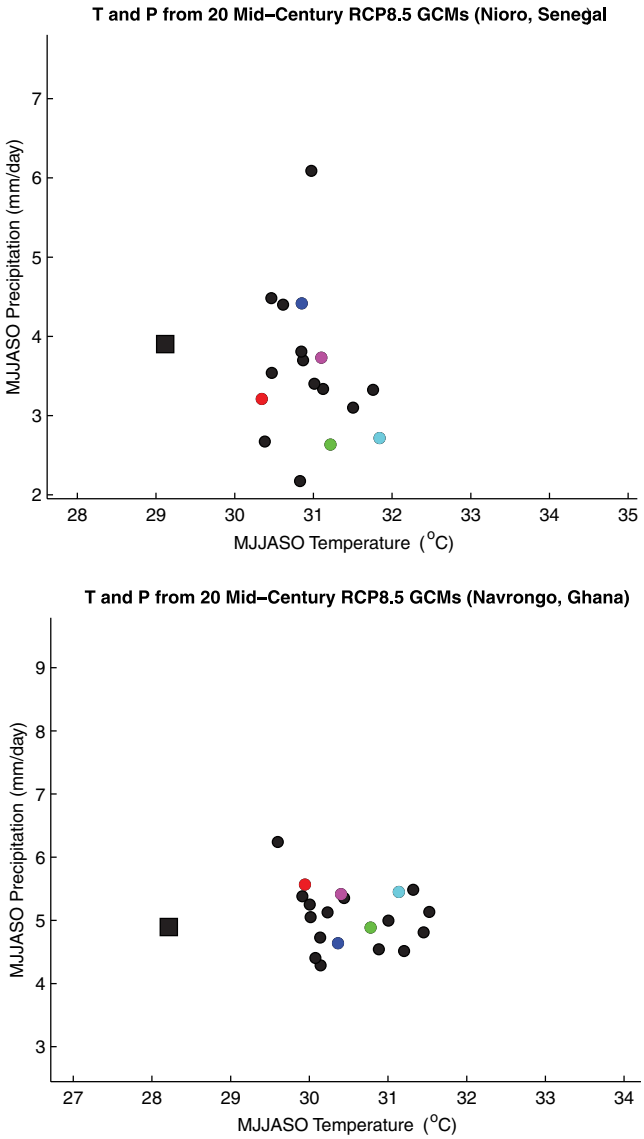


Fig. 7b. CMIP5 GCM projections for temperature and precipitations during the crop growing season (May to October) at Nioro, Senegal, and Navrongo, Ghana. The black square represents the current (1981–2010 baseline) situation, and the colored dots represent the five GCMs considered in the study.

sites, sowing date distributions were constructed from previous studies. Third, fertilizer application rates were derived from application costs, and the application dates were assumed to follow extension advice (i.e., 14 and 42 days after sowing). The main consequence of these assumptions was that it was difficult to match simulated and observed yields directly.

Table 2. Calibration of maize, millet, and peanut cultivars for grain yields.

	APSIM		DSSAT	
	RMSE (kg/ha)	R^2	RMSE (kg/ha)	R^2
Maize (*obatanpa*)	476	0.90	474	0.89
Millet (*CIVT*)	206	0.75	433	0.90
Peanut (*Chinese*)	272	0.90	633	0.95

Crop model results (*DSSAT and APSIM*)

All crop models were successfully calibrated for the test locations. The calibrations showed strong relationships between simulated and observed yields for both APSIM and DSSAT (Table 2). The results confirm that the genetic coefficients are sufficiently accurate to reliably simulate growth and yield of the cultivars in response to the soil and climate environments of West Africa.

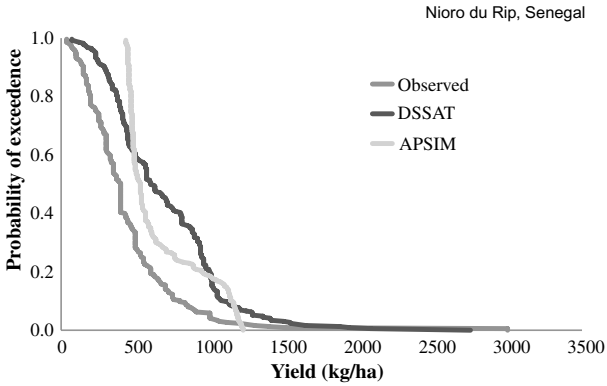
The validations of the crop models for Nioro for the base year (2007) are shown in Fig. 8. The coarse level of the input information prevented a direct matching of simulated and observed yields. For the low yield range of millet, APSIM overestimated the yields, whereas DSSAT captured the distribution well. In the case of maize, APSIM matched the observed distribution well except at the high yield ranges. For peanut, DSSAT underestimated yields while APSIM overestimated yields. However, the probability distributions of observed and simulated yields were similar. Reliable validations were also obtained for Navrongo, Ghana.

Economics

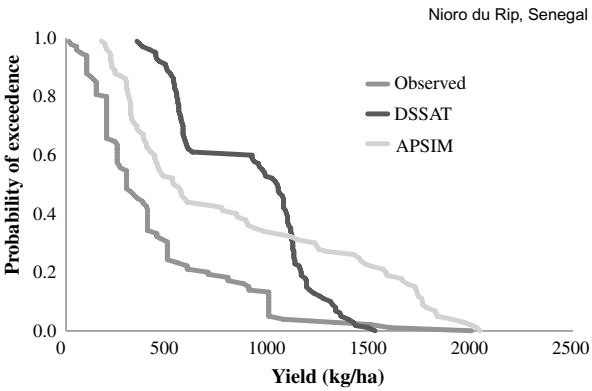
Survey data

A household survey conducted in 2007 at six villages — Djiguimar, Medina Sabakh, Ndiba, Ngayene, Paoskoto, and Porokhane — documented their geo-referenced locations, household size, farm size, stratified cropping systems, cost of manure and fertilizer applications, and crop yields, among other variables. The sowing period spans almost two months from mid-May to mid-July. The total number of farms surveyed was 226, of which 100 cultivated maize (9.6% by area), 223 cultivated peanuts (53% by area), and 226 cultivated millet (37% by area). Socio-economic information for Navrongo was obtained from a survey carried out in 2012 in 16 communities. The same information was collected as in the case of Nioro. The sowing period spans from mid-May to end of July. The total number of households surveyed was 276, of which 74 cultivated maize (16 % by area), 156 cultivated millet (42 % by area), and 237 cultivated peanuts (42 % by area). Information on farm management practices were used as input data for crop modeling in both sides.

(a) Probability of exceedance for millet yield



(b) Probability of exceedance for maize yield



(c) Probability of exceedance for peanut yield

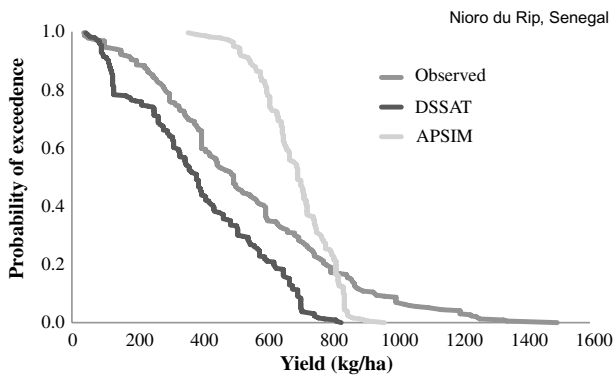


Fig. 8. Validation of crop models at Nioro, Senegal, 2007.

Strata

A major task of this study was to assess the impacts of climate change on agricultural productivity in West Africa. New methodologies and tools were required. First, two subsystems (strata) of farms are considered in both sites. In Nioro, the two strata are non-maize farms (Strata 1) and maize-based farms (Strata 2). Second, the yields for each farm were simulated for the 30 baseline years and the 30 future years for each of the five GCMs, assuming that farmers continue their current practices (base cultivar). Thereafter, future yields were again simulated assuming that farmers adopted new technology (i.e., an adapted cultivar that is heat- and drought-tolerant) as an adaptation strategy to minimize climate change impacts.

The AgMIP methodology is schematically shown in Fig. 9. The ability to simulate multiple farms, management regimes, and years was enabled by the development of innovative AgMIP tools. QuadUI (v1.2.1- Beta24-hf1) is a utility that extracts relevant crop model input data from socio-economic data (i.e., raw survey data) and stores them in Data Overlay Multi-model Export (DOME) files. QuadUI was used to translate survey and DOME files into model-ready formats (i.e., APSIM and DSSAT), which enables multiple model simulations. This resulted in a spatial simulation of crop yields beyond single farms for baseline climate and climate change scenarios. These serve as inputs for the socio-economic model (Tradeoff

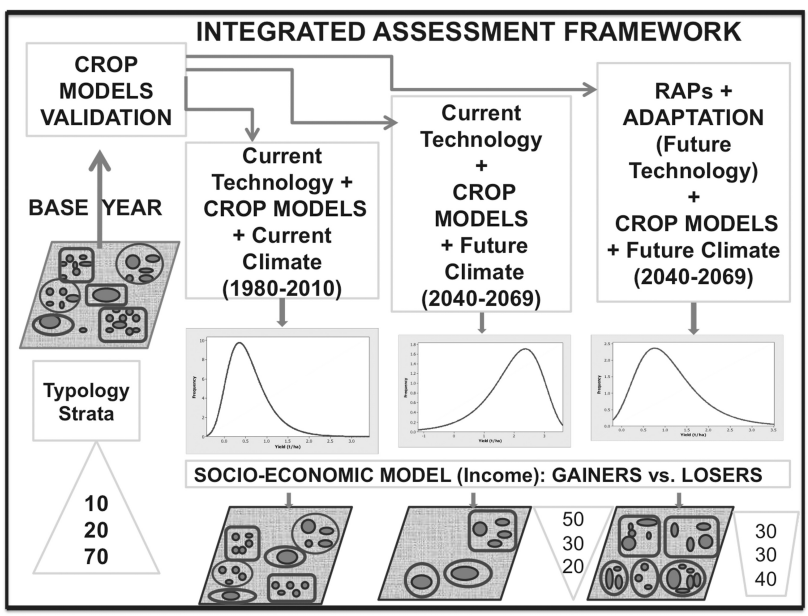


Fig. 9. Schematic representation of the integrated assessment framework.

Analysis Model for Multi-dimensional Impact Assessment; TOA-MD; Antle and Stoorvogel, 2006) to determine changes in the behavior of the farm households under climate change conditions.

To evaluate the ability of the crop models to simulate observed data the root-mean-square error (RMSE), modified coefficient of model efficiency, and correlation coefficient were used. Baseline and projected simulated grain yield data were analyzed by using analysis of variance (ANOVA). Analyses were carried out to compare the performance of base technology with changed technology for the various climate scenarios. A randomized complete block design (RCBD) approach was used to analyze data and the least significant differences were determined at 5% probability to separate means of treatments. Farms were considered as replications and years taken as blocks, as yields under each treatment in a given year were not affected by another year.

RAP narrative and development

RAP 1 assumes that crop production in Nioro will be characterized by short-term agricultural policy intervention/short-term, state-led, urban driven (negative). This RAP 1 assumes dominance of state actors in the agricultural development agenda with the view of bringing in fast short-term gains with food security outcomes to the population. Main interventions will include support for the agricultural service sector, fertilizer subsidies, and feeder roads (slow), trading land and human resources to foreign investors who will in turn develop infrastructure (Table 3).

For Navrongo, crop production will be farmer-led with the adoption of intensive and expanded (I&E) irrigation technology using hand-dug, shallow wells. The RAP 1 for Navrongo assumes that farms located within the WVB with access to irrigation will be better-off following reduced precipitation and increased temperature under future climate. This is because irrigation mutes the negative impacts of climate change on farm systems. Details of parameters used are indicated in Table 3.

Adaptation package

We assumed that farmers in the future will adopt improved technology to adapt cropping systems to the new environment. The development of the changed technology was done within the context of the RAPs, with a focus on new varieties that are heat- and drought-tolerant. Virtual varieties of the crops were simulated by changing the genetic coefficients (for cereals), root distribution parameters, and root-water extraction potentials. Heat tolerance was simulated for the cereals by increasing thermal time from silking to physiological maturity (P5 in DSSAT) by

Table 3. Summary of RAP 1 for Nioro, Senegal with main parameters.

Variables	Direction of change	Magnitude of change	Rationale for direction and magnitude of change	Percent change over the period	Rationale for percent change over period
Household size	Decrease	Medium	Internal migration of young people to the cities, split in households and education (younger people having smaller family sizes).	50%	Education, higher literacy rate of women and migration.
Farm size	Increase	Large	People migrate and the few that stay have more available land to mechanize and increase farm sizes. As farm sizes increase (family size decreasing), farmers have to rely on mechanization and not human labor hence they have to increase farm size.	100%	Minimum farm size for farm hiring labor and machinery.
Non-agricultural income	Increase	Medium	Service sector is developed, farm consolidation (causing people to find alternatives sources of income outside farming).	30%	Development of new labor opportunities, farm labor will shrink.
Production cost	Increase	Small	Increased input cost due to high fuel prices and greater concentration of input providers (e.g., seed providers).	10%	Amount and cost of inputs considering some subsidies, fertilizer being subsidized by the government
Livestock numbers	Increase	Medium	Increased demand, increasing incomes and purchasing power.	55%	Sedentarization trends as cropland extends.
Livestock yield	Increase	Medium	Animal breeding programs, improved animal health programs.	30%	Research development programs, government policies.

10% to restore the lifecycle of the original cultivar under climate change conditions. In APSIM, the percentage increase applied to P5 in DSSAT was calculated on the thermal time from the start of grain-filling to maturity and the increase was added to the thermal time from flowering to maturity. The density of the root distribution of the base cultivars was increased beneath the 20-cm depth. This was done to enable the plant roots to explore more of the soil profile for the uptake of water and nutrient resources as pertains to drought and/or nutrient-stress conditions.

$$\mathrm{WR} = \left(1 - \left(\frac{Z}{1000}\right)\right)^6$$

where z is depth of soil layer and WR is root distribution. The water extraction potential was increased by adjusting the crop-specific lower limit such that total water availability increased by 20%, as described by the following equation (Singh *et al.*, 2013):

$$\mathrm{LL}\left(\mathrm{adapt}\right) = \mathrm{LL} - 0.2(\mathrm{DUL} - \mathrm{LL})$$

where LL(adapt) is the lower limit of soil moisture under adaptation conditions, LL is the original lower limit of the soil, and DUL is the original, drained upper limit of the soil moisture.

Core Question 1: What Is the Sensitivity of Current Agricultural Production Systems to Climate Change?

Impact of climate change on crop production

Maize

Simulated maize yields using DSSAT for the baseline climate were 889 kg/ha and 994 kg/ha for Nioro and Navrongo, respectively. For Nioro, the maize yields simulated for the 2050s under the five GCMs were significantly lower than those of the baseline and ranged from 344 kg/ha for HadGEM2-ES to 600 kg/ha for CCSM. In Navrongo, simulated future yields under all GCMs were significantly ($p < 0.05$) lower than that of the baseline climate (Table 4), with the lowest yield simulated under HadGEM2-ES and the highest under CCSM4. Climate change resulted in yield reductions between 32% and 62% in Nioro and 18% and 35% in Navrongo. Variability in yields simulated under baseline climate in Nioro was 36% while those for the GCMs ranged between 34 and 42% across GCMs. The variability in the simulated baseline climate yields was 50% while those for the GCMs ranged between 48% and 49% across the GCMs in Navrongo.

Table 4. Simulated mean yields of maize, millet, and peanut by DSSAT and APSIM under baseline and current production systems with climate change scenarios without adaptation for Nioro, Senegal, and Navrongo, Ghana.

Nioro	Maize (kg/ha/ha)		Millet (kg/ha)		Peanut (kg/ha)	
Climate scenario	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
BASELINE	889	891	286	758	273	550
GFDL-ESM2M_I	596	800	412	728	258	621
CCSM4_E	600	766	292	697	290	643
MIROC5_O	536	802	304	703	254	601
MPI-ESM-MR_R	390	688	184	630	229	591
HadGEM2-ES_K	344	709	231	653	218	609
LSD (0.05)	61	121	38	31	26	28

Navrongo	Maize (kg/ha/ha)		Millet (kg/ha)		Peanut (kg/ha)	
Climate scenario	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
BASELINE	994	941	433	324	281	432
GFDL-ESM2M _I	701	947	319	325	349	557
CCSM4 _E	804	925	338	295	330	599
MIROC5_O	747	925	313	292	319	556
MPI-ESM-MR_R	698	929	299	381	320	636
HadGEM2-ES_K	641	902	272	286	292	581
LSD (0.05)	123	197	63	23	16	43

For APSIM, simulated maize yield under the baseline climate in Nioro was 891 kg/ha and was significantly higher than those from HadGEM2-ES and MPI-ESM-MR. The other GCMs — GFDL-ESM2M, CCSM4, and MICROC5 — produced lower yields in the 2050s relative to the baseline yields, but the differences were not significant. In Navrongo, simulated baseline grain yield was 941 kg/ha and 2050s yields simulated for the five GCMs ranged between 902 and 947 kg/ha. Grain yields for the GCMs ranged from 688 kg/ha for MPI-ESM-MR to 802 kg/ha for MIROC5 in Nioro. In Navrongo, HadGEM2-ES produced the least yield while GFDL-ESM2M produced the highest yield. Reduction in yield due to climate change was between 9% to 23% for all GCMs in Nioro and between 1% and 4% in Navrongo for all GCMs, except for MIROC5 and MPI-ESM-MR, which produced a yield increment of 1%. Differences observed among GCMs and baselines were, however, not statistically

significant. Variability in simulated baseline climate yield was 56%, while those for the GCMs ranged between 50% to 58% in Nioro. In Navrongo, variability in baseline yield was 67% as against between 63% and 66% across GCMs.

Millet

In Nioro, simulated mean yield of millet was 286 kg/ha under baseline conditions. Yields produced under MPI-ESM-MR and HADGEM2-ES for the 2050s were significantly ($p < 0.05$) lower than the baseline yields while those from the other GCMs were higher than baseline yields. Differences between baseline yields and those obtained from CCSM4 and MIROC5 were not significant. Yields varied across GCMs (Table 4). Yields from GFDL-ESM2M were significantly higher than those from the other GCMs and the baseline. Percentage increment in grain yield was observed in three GCMs and ranged from 4% (MIROC5) to 49% (GFDL-ESM2M) while percentage reductions were observed in two GCMs from 19% (HADGEM2) to 35% (MPI-ESM-MR) in Nioro.

For Navrongo, simulated mean grain under baseline climate was 433 kg/ha and was significantly higher than the yield produced under the five GCMs for the 2050s. Yield reductions simulated under the GCMs ranged between 25% (CCSM4) and 42% (HadGEM2-ES). Variability in yields was very high, ranging from 66% to 75% across GCMs with baseline climate variability of 74% when the DSSAT crop model was used in Nioro. For Navrongo, variability in baseline climate yield was 71% compared with a range of 83% to 95% across the five GCMs.

For APSIM, the mean baseline yield obtained in Nioro was 758 kg/ha, while those obtained under the five GCMs ranged from 630 to 728 kg/ha and were lower than those obtained from the baseline climate except for GFDL-ESM2M which was not significantly different. Simulated reduction in yields ranged from 4% (GFDL-ESM2M) to 16% (MPI-ESM-MR) in Nioro. In Navrongo, simulated mean grain yield under baseline climate was 324 kg/ha and higher than those under CCSM4, HadGEM2-ES, and MIROC5, while GFDL-ESM2M was similar to baseline yields and MPI-ESM-MR produced higher yields. Simulated future yields ranged from 286 kg/ha (HADGEM2-ES) to 381 kg/ha for (MPI-ESM-MR). GFDL-ESM2M and MPI-ESM-MR produced yield increments of 3 and 19% respectively, while yield reductions of between 9 to 12% were simulated for CCSM4, HadGEM2-ES, and MIROC5. Variability in yield in Nioro ranged from 20 to 27% across GCMs compared with a baseline climate variability of 25% for APSIM. In Navrongo, variability in the baseline climate yields was 34%, compared with a range of 26% to 37% across GCMs.

Peanut

In Nioro, peanut yield simulated by DSSAT under baseline climate was 273 kg/ha while simulated yield for the future (2050s) under the five GCMs ranged from 218 (HadGEM2-ES) to 290 kg/ha (CCSM4). This translates into yield reductions ranging from 2% to 17% across GCMs except for CCSM4, which recorded yield increase of 10%. In Navrongo, simulated mean yield of peanut under baseline climate was 281 kg/ha, while mean simulated future yields ranged from 292 (HadGEM2-ES) to 349 kg/ha (GFDL-ESM2M). All the five GCMs showed yield increments of between 5% and 19% over the baseline. Variability in peanut yield was between 53% and 56% across GCMs, compared with the baseline yield variability of 58% in Nioro. In Navrongo, variability in yield ranged between 27% and 28% across GCMs and 33% in the baseline climate.

For APSIM, simulated yield under baseline climate was 550 kg/ha and was significantly lower than those obtained under each of the GCMs in Nioro, ranging from 591 (MPI-ESM-MR) to 643 kg/ha (CCSM4). Yield increments of between 7% and 17% were obtained across GCMs relative to the baseline climate. In Navrongo, simulated baseline climate yield was 432 kg/ha, compared with yields of 556 (MIROC5) to 636 kg/ha (MPI-ESM-MR) across the five GCMs. This translates into yield increments of between 28% and 47%. Variability in yields obtained under the five GCMs was between 23% and 26%, compared with 23% for baseline yields in Nioro. In Navrongo, variability in yields under the baseline climate was 43%, whereas those across the GCMs were between 39% and 45%.

Discussion

The effects of climate change on yields relative to baseline climates were generally negative for the cereal crops (i.e., millet and maize), irrespective of the crop simulation model. This can be attributed to increases in temperature during the growing period and differences in the total rainfall amounts relative to those of the baseline climate. However, yield reductions simulated for maize by APSIM in Navrongo were not significantly different from that of the baseline. Similarly, both models simulated similar yields to the baseline yields under some GCMs. In the case of peanut, yield increases were simulated at both sites by both models except for CCSM4, under which DSSAT simulated a yield increase which was not significantly different from that of the baseline. Even though CCSM4 projected lower future rainfall amounts relative to that of the baseline in Nioro, it had the lowest temperature increase; hence, lower reductions in yields were simulated by both models. Similar

observations were made for Navrongo. Of all the five GCMs, MPI-ESM-MR and HadGEM2-ES resulted in the lowest yield projections for all three crops. This may be due to the lower total rainfall amounts, low daily intensity recorded during the growing season in the case of MPI-ESM-MR, coupled with a higher temperature regime that characterized these GCMs (Figs. 6a and 6b). The effect of temperature in reducing crop yield has been reported by several studies (Mearns *et al.*, 1984; Moriondo *et al.*, 2011) and has been described as having the most adverse effect on crop yield among all weather parameters. Certain stages of crop growth are particularly sensitive to temperature change. Increased temperatures above certain thresholds for most crops during the reproductive stage can result in significant yield loss through its effect on grain-filling, grain numbers, and even sterility. It also exerts stress on the crop through high evapotranspiration and energy demands that otherwise would result in crop production but are instead used to manage the stress.

The extent of the changes in crop yield due to projected future climate did vary between the crops models. For instance with millet, the impact of climate change on grain yield varied from 11% to 44% for DSSAT and from 5% to 19% for APSIM. Similar observations can be made in the case of maize and peanut. The extent to which the two models respond to temperature and increased rainfall varied, which also resulted in differences in model outcomes. The effect of climate change was higher in Nioro than Navrongo using both crop simulation models. Additionally, the effect of climate change on grain yield was generally higher with DSSAT than with APSIM.

Differences in the extent of climate change impact predictions on yield by the crop models may be attributed to the different approaches they employ in simulating yield. For instance, DSSAT uses two main genetic coefficients (P1 and P5) to describe maize phenology, whereas APSIM uses as many as seven genetic coefficients. Further, APSIM simulation of millet considers each tiller as a separate plant, which thus complicates the calibration procedure since such detailed data are not available in the calibration datasets used in this study. Also, the life-cycle description of cereals in DSSAT is independent of environmental stresses such as water and nutrient deficiencies, but these are captured by APSIM. Given that a shift in phenology may result in sensitive stages in crop growth coinciding with favorable or less favorable weather conditions, these differences in approach could explain the outcomes of the two crop models. Both models, however, agree on the direction of impacts under future climate change scenarios with baseline technology. In spite of the lower impact of climate change on crop

production in Navrongo, variability in yields was much higher than for Nioro. This could be attributed in part to the poorer soils in Navrongo compared to those in Nioro.

Economic impact of climate change on current production systems

The economic part of this assessment first explores how the current climate affects selected economic outcomes in Nioro without adaptation. Due to the lower future yields simulated by DSSAT and APSIM, most economic indicators would decline under climate change without adaptation. Whereas APSIM seems to project less variability in net returns irrespective of stratum, DSSAT shows considerable variations in net returns. In Nioro the aggregate results show that estimated mean net returns per farm, using simulated yields, decrease from the DSSAT model between 10% and 38% (Table 5). The impact of climate change is greater for maize-based farms (Stratum 2) as their estimated mean net returns per farm decrease between 13% (reduction from $2376 to $2075) to 41% (decrease from $2376 to $1411) for the same climate scenarios.

In the case of APSIM, the results are similar although there is less variability. In the aggregate, the impact of climate change on net returns is negative, varying between 10 and 19%.

By considering two climate scenarios (GCM CCSM4 and GCM HadGEM2-ES), with DSSAT, as an illustration, we notice the following: For GCM CCSM4, gains per farm amount to $40 while losses reach $323, which results in net losses per farm of $283; for GCM HadGEM2-ES, gains per farm are only $7 whereas losses amount to $636 for a net loss per farm of $629. Figures 10a and 10b show the gains, losses, and net impacts as a percent of mean net farm returns.

Assuming no adaptation, the impacts of climate change on *per capita* income and poverty rates in Nioro are also largely negative.

The GCMs, MPI-ESM-MR and HadGEM2-ES display the greatest negative values. With DSSAT, *per capita* income decreases on average by 15%, i.e. $45 with a minimum of $19 and a maximum of $69 (Fig. 11). Without climate change, the poverty rate reaches about 73% on aggregate, with 82% displayed in Stratum 1 (non-maize farms) and 64% in Stratum 2 (maize-based farms). Climate change without adaptation results in a higher level of poverty under both models for maize-based farms. Non maize farms, however, experience a smaller impact under both DSSAT and APSIM.

Table 5. Climate sensitivity of current agricultural production systems for Nioro, Senegal.

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Observed mean yield (millet) (kg/ha)	786	786	786	786	786	786	786	786	786	786
Mean yield change (millet) (%)	8	8	49	3	−18	−4	4	3	−34	−7
Observed mean yield (penaut) (kg/ha)	956	956	956	956	956	956	956	956	956	956
Mean yield change (peanut) (%)	13	15	0	11	−15	9	−2	7	−11	5
Observed mean yield (maize) (kg/ha)	—	—	—	—	—	—	—	—	—	—
Mean yield change (maize) (%)	—	—	—	—	—	—	—	—	—	—
Losers (%)	71	69	58	74	92	78	83	77	94	82
Gains (% mean net returns)	4.0	4.2	6.3	3.3	0.7	2.6	1.8	2.9	0.5	2.2
Losses (% mean net returns)	−16.6	−15.0	−10.7	−17.2	−31.2	−19.5	−20.6	−18.5	−34.6	−21.5
Net impact (% mean net returns)	−12.6	−10.8	−4.5	−13.9	−30.5	−16.8	−18.8	−15.5	−34.0	−19.3
Projected net returns without climate change (US$)	1308	1308	1308	1308	1308	1308	1308	1308	1308	1308
Projected net returns with climate change (US$)	1143	1167	1250	1127	909	1088	1062	1105	863	1055
Change in mean net returns	−13%	−11%	−4%	−14%	−30%	−17%	−19%	−16%	−34%	−19%
Projected *per capita* income without climate change (US$)	249	249	249	249	249	249	249	249	249	249

(*Continued*)

Table 5. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected *per capita* income with climate change (US$)	232	234	243	230	207	226	223	228	202	222
Percent change in *per capita* income	−7%	−6%	−2%	−8%	−17%	−9%	−10%	−9%	−19%	−11%
Observed poverty rate without climate change (%)	82.6	82.6	82.6	82.3	82.6	82.3	82.6	82.3	82.6	82.3
Projected poverty rate with climate change (%)	85.0	84.8	83.5	85.7	90.0	86.4	87.2	86.1	90.7	87.1
Change in poverty rate	2.4	2.2	0.9	3.4	7.4	4.2	4.5	3.8	8.1	4.8
Maize farms										
Observed mean yield (millet) (kg/ha)	857	857	857	857	857	857	857	857	857	857
Mean yield change (millet) (%)	6	11	52	7	−22	−8	5	2	−38	−10
Observed mean yield (penaut) (kg/ha)	894	894	894	894	894	894	894	894	894	894
Mean yield change (peanut) (%)	6	17	−5	13	−20	11	−7	10	−16	8
Observed mean yield (maize) (kg/ha)	2025	2025	2025	2025	2025	2025	2025	2025	2025	2025
Mean yield change (maize) (%)	−32	−15	−34	−10	−62	−18	−41	−9	−57	−23
Losers (%)	88	72	78	68	98	77	96	71	98	80

(*Continued*)

Table 5. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Gains (% mean net returns)	0.9	3.0	2.2	4.2	0.2	2.9	0.3	3.9	0.2	2.5
Losses (% mean net returns)	−19.7	−12.7	−14.9	−14.3	−40.0	−19.1	−28.6	−15.8	−40.8	−21.6
Net impact (% mean net returns)	−18.8	−9.8	−12.7	−10.0	−39.9	−16.1	−28.3	−11.9	−40.6	−19.2
Observed net returns without climate change (US$)	2376	2376	2376	2376	2376	2376	2376	2376	2376	2376
Projected net returns with climate change (US$)	1931	2144	2075	2138	1429	1993	1703	2093	1411	1921
Change in mean net returns	−19%	−10%	−13%	−10%	−40%	−16%	−28%	−12%	−41%	−19%
Observed *per capita* income without climate change (US$)	341	341	341	341	341	341	341	341	341	341
Projected *per capita* income with climate change (US$)	299	319	313	319	252	305	278	315	250	298
Percent change in *per capita* income	−12%	−6%	−8%	−7%	−26%	−11%	−19%	−8%	−27%	−13%
Observed poverty rate without climate change (%)	63.9	64.0	64.0	63.2	64.0	63.2	64.0	63.2	64.0	63.2
Projected poverty rate with climate change (%)	73.2	68.4	69.8	68.6	84.3	71.8	78.1	69.6	84.7	73.3
Change in poverty rate	9.3	4.4	5.8	5.4	20.4	8.6	14.2	6.5	20.8	10.2

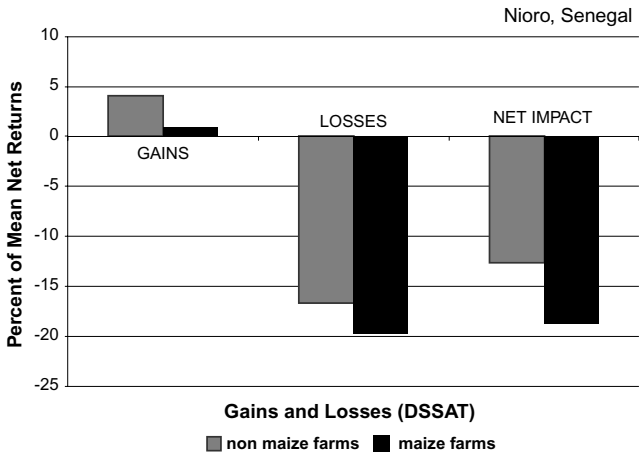
(*Continued*)

Table 5. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
All farms										
Losers (%)	80	71	68	71	95	78	90	74	96	81
Gains (% mean net returns)	2.3	3.5	4.0	3.9	0.4	2.8	0.9	3.5	0.3	2.3
Losses (% mean net returns)	−18.4	−13.7	−13.1	−15.5	−36.2	−19.2	−25.2	−16.9	−38.1	−21.6
Net impact (% mean net returns)	−16.1	−10.2	−9.1	−11.7	−35.8	−16.4	−24.2	−13.5	−37.8	−19.2
Observed net returns without climate change (US$)	1757	1757	1772	1757	1757	1757	1757	1757	1757	1757
Projected net returns with climate change (US$)	1474	1578	1597	1552	1128	1468	1331	1520	1093	1419
Change in mean net returns	−16%	−10%	−10%	−12%	−36%	−16%	−24%	−13%	−38%	−19%
Observed *per capita* income without climate change (US$)	295	295	297	295	295	295	295	295	295	295
Projected *per capita* income with climate change (US$)	265	277	278	274	230	265	250	271	226	260
Percent change in *per capita* income	−10%	−6%	−6%	−7%	−22%	−10%	−15%	−8%	−23%	−12%
Observed poverty rate without climate change (%)	73.3	73.3	73.3	72.7	73.3	72.7	73.3	72.7	73.3	72.7
Projected poverty rate with climate change (%)	79.1	76.6	76.6	77.1	87.2	79.1	82.6	77.9	87.7	80.2
Change in poverty rate	5.8	3.3	3.3	4.4	13.9	6.4	9.4	5.1	14.4	7.5

NB: Poverty line is equal to FCFA204845, i.e., US$ 409.69 (1$=500 FCFA).

(a) GCM CCSM4



(b) GCM HadGEM2-ES

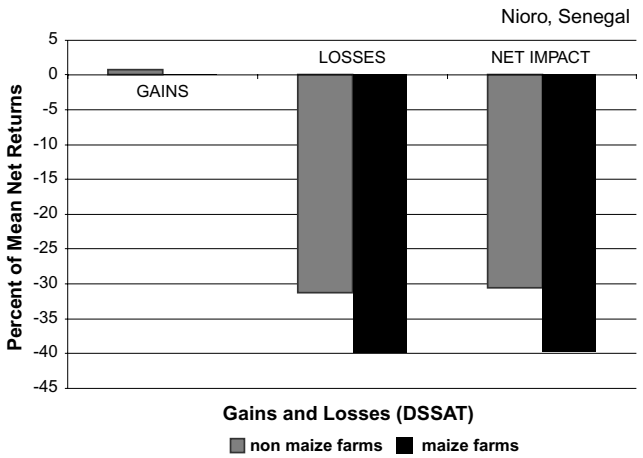


Fig. 10. Gains, losses, and net impact on farmers' livelihoods in Nioro, Senegal with CCSM4 and HadGEM2-ES climate change scenarios.

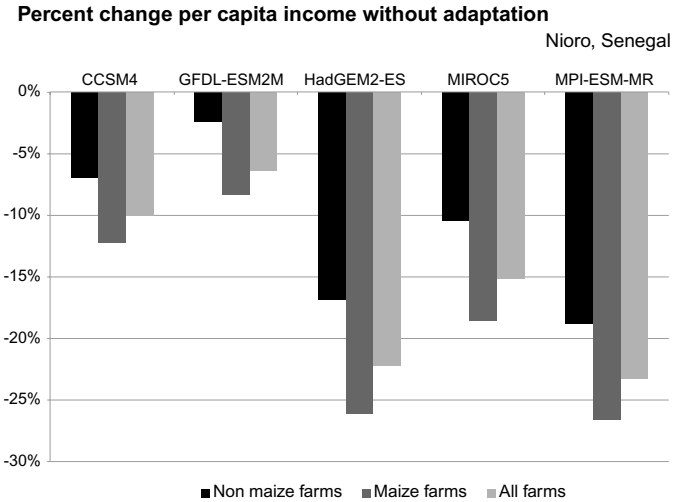


Fig. 11. Effect of climate change without adaptation on the percentage change of *per capita* income of farmers in Nioro, Senegal.

Core Question 2: What Is the Impact of Climate Change on Future Agricultural Production Systems?

Results and discussion

Our interest in this question is to assess the economic impact of climate change on farms in Nioro when autonomous yield and price trends are accounted for as the current production system continues. We use IFPRI IMPACT model data to estimate the percent changes from 2005–2050 for the no climate change yield trend. We also use these simulated Impact data to project trends in prices. Table 6 gives the yield growth trend factor and the price trend for the three crops used in the estimation. Note that, in the absence of millet in the impact data, sorghum trends are used instead. In the RAP 1 for Nioro, we assumed a 30% increase in non-agricultural income, 100% increase in farm size, 50% decrease in household size, and 10% increase in costs of production. These factors combine to increase net farm returns substantially and decrease poverty rates.

Under these assumptions, the results of the TOA-MD simulations assuming autonomous trends in crop yield, price, and production cost show an overall better picture than the case of climate change effects on current productions systems without adaptation for Nioro. With DSSAT, farmers still witness declines in their returns with two climate models (HadGEM2-ES and MPI-ESM-MR). Improvements are dramatic with APSIM. Specifically, we note a decrease in the percentage of farms that lose from climate change (between 68% and 96% under current productions

Table 6. Trend factors for yields and prices for selected crops in Senegal.

	Senegal	
Crop	Yield	Price
Maize	1.905	2.218
Peanut	1.164	1.222
Sorghum	1.417	1.578

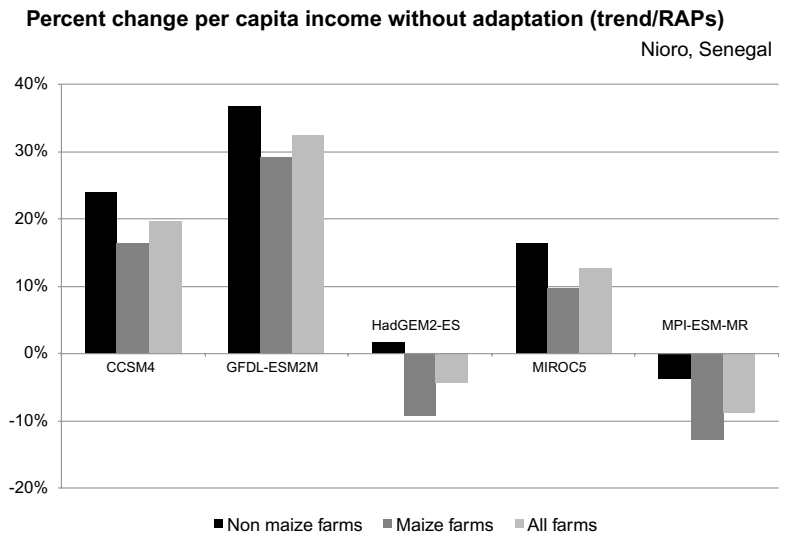


Fig. 12. Effect of climate change without adaptation but with trends and RAPs on the percentage *per capita* income of farmers in Nioro, Senegal.

systems to between 14% and 70% under future production systems with DSSAT; between 71 and 81% to 10 to 15% with the APSIM model).

Additionally, net impacts as a percent of mean net farm returns are mostly positive (between 5% and 44% for DSSAT, while under APSIM net gains vary from 1% to 12%). Shifting from current to future agricultural systems, it appears that trend factors will have significant positive impacts which may offset some of the impact of climate change. For instance, poverty rates drop dramatically by more than 60 points for non-maize-based farms, while the decrease is about 52 points for maize-based farms. *Per capita* income increases between 17% and 47% for all GCMs under APSIM when effects of climate change and trend factors are projected for the future agricultural system. The data for the DSSAT model show similar results for HadGEM2-ES, GFDL-ESM2M, and MIROC5. In contrast, the results for CCSM4 and MPI-ESM-MR are slightly lower and negative (Fig. 12 and Table 7).

Table 7. Impact of climate in future without adaptation for the Nioro, Senegal cropping system.

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected mean yield (millet) (kg/ha)	1114	1114	1114	1114	1114	1114	1114	1114	1114	1114
Mean yield change (millet) (%)	8	8	49	3	−18	−4	4	3	−34	−7
Projected mean yield (peanut) (kg/ha)	1103	1103	1103	1103	1103	1103	1103	1103	1103	1103
Mean yield change (peanut) (%)	14	16	1	12	−14	10	−1	8	−10	6
Projected mean yield (maize) (kg/ha)	—	—	—	—	—	—	—	—	—	—
Mean yield change (maize) (%)	—	—	—	—	—	—	—	—	—	—
Losers (%)	15	2	9	2	45	20	20	2	60	3
Gains (% mean net returns)	35.8	100.3	52.6	93.0	9.8	27.3	25.8	89.3	5.8	78.7
Losses (% mean net returns)	−2.5	−0.4	−1.7	−0.4	−7.3	−3.3	−3.1	−0.4	−11.0	−0.4
Net impact (% mean net returns)	33.3	99.9	50.9	92.6	2.5	24.0	22.7	88.8	−5.2	78.3
Projected net returns without climate change (US$)	3560	2396	3560	2396	3560	3560	3560	2396	3560	2396
Projected net returns with climate change (US$)	4747	4791	5373	4617	3649	4416	4369	4525	3376	4272
Change in mean net returns	33%	100%	51%	93%	2%	24%	23%	89%	−5%	78%
Projected *per capita* income without climate change (US$)	1039	794	1039	794	1039	1039	1039	794	1039	794

(*Continued*)

Table 7. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected *per capita* income with climate change (US$)	1289	1298	1421	1261	1058	1219	1209	1242	1000	1189
Percent change in *per capita* income	24%	64%	37%	59%	2%	17%	16%	56%	−4%	50%
Projected poverty rate without climate change (%)	16.4	25.9	16.4	25.9	16.4	16.4	16.4	25.9	16.4	25.9
Projected poverty rate with climate change (%)	13.3	13.2	11.8	13.6	16.5	14.2	16.4	14.0	17.7	14.6
Change in poverty rate	−3.1	−12.6	−4.6	−12.2	0.1	−2.2	0.0	−11.9	1.3	−11.3
Maize farms										
Projected mean yield (millet) (kg/ha)	1214	1214	1214	1214	1214	1214	1214	1214	1214	1214
Mean yield change (millet) (%)	6	11	52	7	−22	−8	5	2	−38	−10
Projected mean yield (peanut) (kg/ha)	1041	1041	1041	1041	1041	1041	1041	1041	1041	1041
Mean yield change (peanut) (%)	6	17	−5	13	−20	11	−7	10	−16	8
Projected mean yield (maize) (kg/ha)	3858	3858	3858	3858	3858	3858	3858	3858	3858	3858
Mean yield change (maize) (%)	−32	−15	−34	−10	−62	−18	−41	−9	−57	−23
Losers (%)	22	18	17	19	72	24	30	20	79	27
Gains (% mean net returns)	24.7	36.8	41.9	35.3	3.4	24.9	17.3	31.4	2.5	21.1

(*Continued*)

Table 7. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Losses (% mean net returns)	−3.5	−3.5	−3.8	−3.7	−15.3	−4.0	−4.7	−3.6	−19.0	−4.6
Net impact (% mean net returns)	21.3	33.3	38.1	31.6	−11.9	20.9	12.6	27.8	−16.5	16.5
Projected net returns without climate change (US$)	5482	5482	5482	5482	5482	5482	5482	5482	5482	5482
Projected net returns with climate change (US$)	6648	7310	7568	7214	4829	6628	6173	9608	4576	6389
Change in mean net returns	21%	33%	38%	32%	−12%	21%	13%	75%	−17%	17%
Projected *per capita* income without climate change (US$)	1338	1338	1338	1338	1338	1338	1338	1338	1338	1338
Projected *per capita* income with climate change (US$)	1557	1682	1731	1664	1215	1554	1468	2114	1167	1509
Percent change in *per capita* income	16%	26%	29%	24%	−9%	16%	10%	58%	−13%	13%
Projected poverty rate without climate change (%)	11.9	11.9	11.9	11.9	11.9	11.9	11.9	11.9	11.9	11.9
Projected poverty rate with climate change (%)	11.0	10.9	11.0	11.1	12.9	11.4	11.6	11.1	13.6	11.7
Change in poverty rate	−0.9	−1.0	−0.9	−0.8	1.0	−0.5	−0.3	−0.8	1.7	−0.2

(*Continued*)

Table 7. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
All farms										
Losers (%)	19	10	14	11	59	12	25	11	70	15
Gains (% mean net returns)	30.0	60.7	47.0	57.0	6.4	26.0	21.3	53.2	4.0	42.8
Losses (% mean net returns)	−3.0	−2.3	−2.8	−2.4	−11.5	−3.6	−4.0	−2.4	−15.2	−3.0
Net impact (% mean net returns)	27.0	58.4	44.1	54.5	−5.1	22.4	17.4	50.7	−11.2	39.8
Projected net returns without climate change (US$)	4368	3694	4368	3694	4368	4368	4368	3694	4368	3694
Projected net returns with climate change (US$)	5546	5850	6296	5708	4145	5346	5127	5568	3880	5162
Change in mean net returns	27%	58%	44%	55%	−5%	22%	17%	51%	−11%	40%
Projected *per capita* income without climate change (US$)	1188	1066	1188	1066	1188	1188	1188	1066	1188	1066
Projected *per capita* income with climate change (US$)	1423	1490	1576	1463	1136	1386	1339	1433	1084	1349
Percent change in *per capita* income	20%	40%	33%	37%	−4%	17%	13%	34%	−9%	27%
Projected poverty rate without climate change (%)	14.2	18.9	14.2	18.9	14.2	14.2	14.2	18.9	14.2	18.9
Projected poverty rate with climate change (%)	12.1	12.1	11.4	12.4	14.7	12.8	12.9	12.5	15.6	13.1
Change in poverty rate	−2.0	−6.8	−2.7	−6.5	0.5	−1.4	−1.3	−6.3	1.5	−5.8

NB: The poverty line is equal to FCFA204845, i.e., US$ 409.69 (1$=500 FCFA).

Core Question 3: What Are the Benefits of Climate Change Adaptations?

Impact of adaptation on crop productivity

Maize

Maize yields simulated by DSSAT based on the use of adapted cultivar ranged from 433 kg/ha for HadGEM2-ES to 766 kg/ha for CCSM4 in Nioro, and from 791 kg/ha for HadGEM2-ES to 995 kg/ha for CCSM4 for Navrongo (Table 8). Comparison between grain yields with and without the use of adapted cultivar indicates yield increments of between 29% and 30% in Nioro, which are different from those obtained for Navrongo (33% and 34%). In Nioro, the statistical analysis indicated that maize yields with the adapted cultivar under the five GCMs were significantly lower ($p < 0.05$) than the yields under the baseline climate and baseline cultivar. The variability in the yield of adapted cultivar was between 29% and 37% in the case of Nioro and between 41% and 43% in Navrongo.

For APSIM, the simulated yields based on the use of adapted cultivar in Nioro ranged from 948 to 1123 kg/ha, while those of Navrongo ranged from 988 kg/ha to

Table 8. Simulated mean yield of maize, millet, and peanut by DSSAT and APSIM under future climate scenarios with the use of adaptation technology for Nioro, Senegal and Navrongo, Ghana.

Nioro	Maize (kg/ha)		Millet (kg/ha)		Peanut (kg/ha)	
Climate scenario	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
GFDL-ESM2M_I	751	1123	587	907	291	691
CCSM4_E	766	1049	393	882	327	716
MIROC5_O	673	1123	424	924	288	672
MPI-ESM-MR_R	493	968	241	858	259	663
HadGEM2-ES_K	433	948	291	848	246	683
LSD (0.05)	66	134	48	31	28.1	29

Navrongo	Maize (kg/ha)		Millet (kg/ha)		Peanut (kg/ha)	
Climate scenario	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
GFDL-ESM2M_I	865	1030	446	409	388	643
CCSM4_E	995	1006	484	393	368	604
MIROC5_O	924	995	450	393	357	598
MPI-ESM-MR_R	860	1017	418	469	357	681
HadGEM2-ES_K	791	988	385	383	328	624
LSD (0.05)	130	213	77	19	16	26

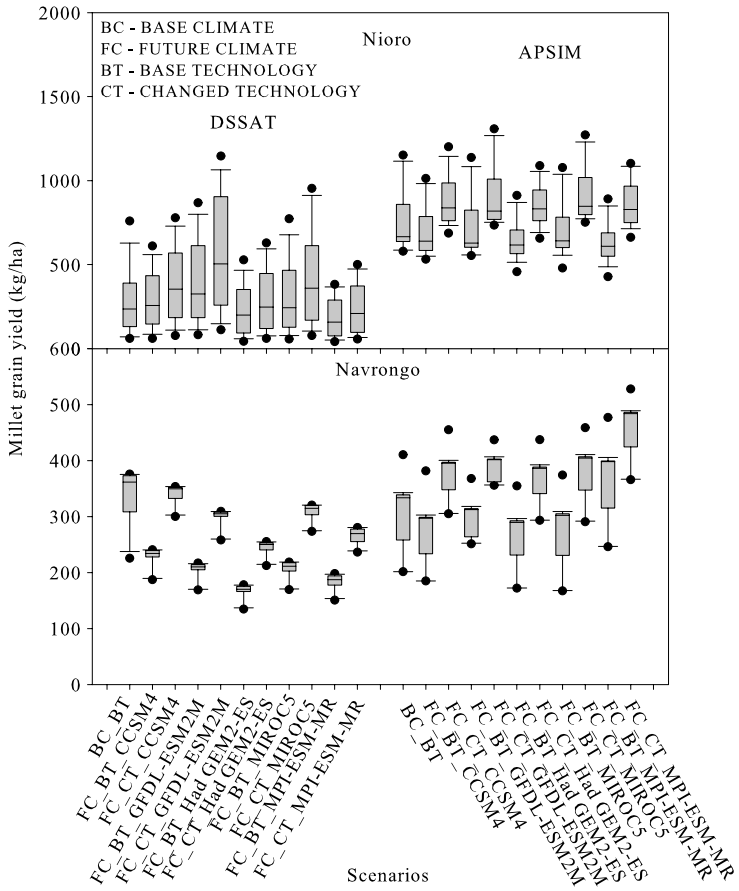


Fig. 13. Simulated variability in millet yields with current base technology (BT) compared to adapted future changed technology (CT) under climate change scenarios for Nioro, Senegal and Navrongo, Ghana.

1030 kg/ha. These translate into yield increments of between 48% (HadGEM2-ES) to 50% (GFDL-ESM2M) in Nioro and from 9% (MIROC5) to 12% (HadGEM2-ES) in Navrongo. HadGEM2-ES produced the lowest grain yields while GFDL-ESM2M and MIROC5 produced the highest grain yields in Nioro. Simulated yield variability of the adapted cultivar was higher (64% to 66%) in Navrongo than in Nioro (44% to 48%). The magnitude of the impact of the adaptation package varied across sites and crop models.

Millet

In Nioro, the yield of millet with the adapted cultivar simulated by DSSAT ranged from 241 kg/ha to 587 kg/ha while those for Navrongo ranged between 385 to

484 kg/ha. The lowest and highest yields were obtained from MPI-ESM-MR and GFDL-ESM2M, respectively, for Nioro, whereas at Navrongo, HadGEM2-ES and MIROC5 showed the lowest and highest yields respectively. The direction of impact of the adapted cultivar was the same between sites, whereas the magnitude of the impact differed (Fig. 13). Comparison between yields for current system with climate change scenario with and without adaptation indicates a yield increase of between 28% and 44% in Nioro and from 32% to 34% in Navrongo. Variability in yields with adapted cultivar was high for Nioro, ranging from 63% to 73% and from 41% to 43% for Navrongo.

Simulated millet yields for APSIM using adapted cultivar ranged from 848 to 924 kg/ha in Nioro and between 383 and 469 kg/ha in Navrongo. The least and the highest yields were obtained with HadGEM2-ES and MIROC5, respectively, for Nioro and HadGEM2-ES and MPI-ESM-MR, respectively, for Navrongo. Using future climate projections with and without adaption resulted in yield increases of between 26% and 39% in Nioro and between 10% and 11% in Navrongo. Variability in simulated yields with the adapted cultivar ranged from 16% to 21% for Nioro and from 64% to 66 % for Navrongo. Simulated yields for all GCMs with the use of adapted cultivar were significantly higher than those with the base cultivar for both sites and models.

Peanut

Simulated yields of peanut using DSSAT for both sites ranged between 246 to 327 kg/ha across GCMs for Nioro and 328 kg/ha to 388 kg/ha for Navrongo. A comparison between yields obtained for current production system with climate change scenarios with and without adaptation indicates yield increments of 18% for Nioro and between 12 and 13% for Navrongo. The lowest yield was produced by HadGEM2-ES at both sites while the highest yields were from CCSM4 and GFDL-ESM2M for Nioro and Navrongo, respectively. Variability in the yields was lower in Navrongo with values between 23% and 25 % across the GCMs while it ranged from 51% to 54% in Nioro.

For APSIM, simulated yields ranged from 663 to 716 kg/ha across GCMs for Nioro and between 598 kg/ha and 681 kg/ha for Navrongo. Comparisons of yields obtained with and without the use of adapted cultivars indicate yield increases of 7% to 8% at both sites. Variability in yields of adapted cultivar was similar on both sites (22% to 24% in Nioro and 39% to 45% in Navrongo). The highest yield was attained under CCSM4 and MPI-ESM-MR while the lowest yields were simulated under MPI-ESM-MR and MIROC5 for Nioro and Navrongo, respectively. Variability in the yield of adapted cultivar was higher with for APSIM compared to DSSAT. While the impact of adaptation was positive in both models, the magnitudes of the effects

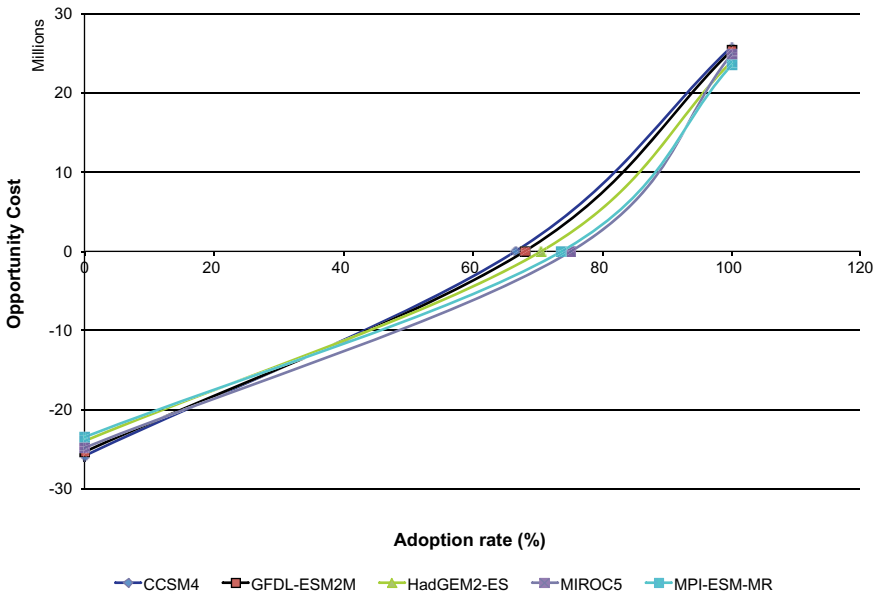


Fig. 14. Opportunity cost and adoption rate for adaptation package simulated with DSSAT under climate change scenarios for Nioro, Senegal.

varied between sites and were not consistent among the crops simulated. Both crop models simulated a general increase in yield and also positive effects of adaptation strategies under future systems (use of adapted cultivars).

Impact of adaptation on farmers' livelihoods

When adaptation to climate change is possible, we notice a dramatic positive change in all the economic indicators in Nioro. A majority of farmers are now better off in all the economic indicators examined. For Nioro, under DSSAT, the adaptation process results in at least 68% of farms that adopt the adaptation package. Adoption rates vary between 68% and 78% (Table 9 and Fig. 14).

Mean net returns per farm increase between 12% and 22% with DSSAT and between 10% and 19% with APSIM. Under the APSIM model, *per capita* income increases on average by $163 (i.e., 11%) and reaches a maximum increase of $217 (i.e., 15%; Fig. 15). There is more dispersion with inputs from DSSAT simulations. *Per capita* income increases 13% on average. Poverty rates display record low levels, between 11% and 14%. This is because poverty drops by large proportions with both crop models.

Table 9. The benefits of climate change adaptations for the Nioro, Senegal cropping system.

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected mean yield without adaptation (millet) (kg/ha)	1202	1199	1656	1150	915	1071	1159	1143	736	1032
Mean yield change (millet) (%)	36	22	44	25	29	29	40	31	35	35
Projected mean yield without adaptation (peanut) (kg/ha)	1253	1282	1113	1239	948	1210	1088	1195	991	1173
Mean yield change (peanut) (%)	19	12	18	12	18	13	19	12	18	13
Projected mean yield without adaptation (maize) (kg/ha)	—	—	—	—	—	—	–	—	—	—
Mean yield change (maize) (%)	—	—	—	—	—	—	—	—	—	—
% adoption rate	80	66	75	68	68	71	74	72	69	74
Projected net returns without adaptation (US$)	4778	4822	5404	4647	3680	4446	4400	4556	3406	4303
Projected net returns with adaptation (US$)	5900	5269	6524	5142	4152	5020	5207	5174	3910	4965
Change in mean net returns	23%	9%	21%	11%	13%	13%	18%	14%	15%	15%
Projected *per capita* income without adaptation (US$)	1295	1305	1427	1268	1064	1226	1216	1249	1007	1195

(*Continued*)

Table 9. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected *per capita* income with adaptation (US$)	1532	1399	1663	1372	1164	1346	1386	1379	1113	1335
Percent change in *per capita* income	18%	7%	17%	8%	9%	10%	14%	10%	11%	12%
Projected poverty rate without adaptation (%)	13.2	13.1	11.7	13.5	16.3	14.1	14.0	13.8	17.5	14.4
Projected poverty rate with adaptation (%)	11.7	12.3	10.4	12.5	15.0	12.8	12.5	12.5	16.0	12.8
Change in poverty rate	−1.4	−0.8	−1.3	−1.0	−1.3	−1.3	−1.5	−1.4	−1.5	−1.6
Maize farms										
Projected mean yield without adaptation (millet) (kg/ha)	1290	1352	1845	1301	953	1123	1269	1235	752	1087
Mean yield change (millet) (%)	35	17	44	15	27	28	40	30	32	35
Projected mean yield without adaptation (peanut) (kg/ha)	1107	1219	985	1177	830	1154	967	1140	872	1121
Mean yield change (peanut) (%)	14	12	14	12	14	13	14	12	14	13
Projected mean yield without adaptation (maize) (kg/ha)	2632	3274	2545	3479	1462	3148	2289	3511	1669	2954

(*Continued*)

Table 9. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Mean yield change (maize) (%)	26	44	36	47	30	38	30	47	31	48
% adoption rate	77	67	73	68	67	70	72	78	69	73
Projected net returns without adaptation (US$)	6713	7438	7694	7340	4938	6751	6291	6753	4683	6510
Projected net returns with adaptation (US$)	8094	8284	9297	8216	5465	7724	7378	8368	5280	7706
Change in mean net returns	21%	11%	21%	12%	11%	14%	17%	24%	13%	18%
Projected *per capita* income without adaptation (US$)	1570	1706	1754	1688	1235	1577	1490	1577	1187	1531
Projected *per capita* income with adaptation (US$)	1829	1865	2056	1852	1335	1760	1695	1881	1300	1756
Percent change in *per capita* income	17%	9%	17%	10%	8%	12%	14%	19%	9%	15%
Projected poverty rate without adaptation (%)	10.9	10.7	10.8	10.8	12.5	11.1	11.3	11.8	13.2	11.4
Projected poverty rate with adaptation (%)	10.4	11.0	11.4	11.0	12.4	11.3	11.5	11.0	13.0	11.4
Change in poverty rate	−0.5	0.3	0.6	0.2	−0.1	0.2	0.2	−0.8	−0.2	0.0

(*Continued*)

Table 9. (*Continued*)

Non-maize Farms	GCM E = CCSM4		GCM I = GFDL-ESM2M		GCM K = HadGEM2-ES		GCM O = MIROC5		GCM R = MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
All farms										
Adoption rate (%)	78	67	74	68	68	71	73	75	69	74
Projected net returns without adaptation (US$)	5591	5922	6367	5779	4209	5415	5195	5479	3943	5231
Projected net returns with adaptation (US$)	6822	6536	7690	6434	4704	6157	6120	6517	4486	6117
Change in mean net returns	22%	10%	21%	11%	12%	14%	18%	19%	14%	17%
Projected *per capita* income without adaptation (US$)	1432	1505	1591	1478	1150	1401	1353	1413	1097	1363
Projected *per capita* income with adaptation (US$)	1681	1632	1860	1612	1249	1553	1540	1630	1206	1546
Percent change in *per capita* income	17%	8%	17%	9%	9%	11%	14%	15%	10%	13%
Projected poverty rate without adaptation (%)	12.0	11.9	11.2	12.2	14.4	12.6	12.7	12.8	15.4	12.9
Projected poverty rate with adaptation (%)	11.1	11.6	10.9	11.7	13.7	12.0	12.0	11.7	14.5	12.1
Change in poverty rate	−1.0	−0.3	−0.3	−0.4	−0.7	−0.6	−0.7	−1.1	−0.9	−0.8

NB: The poverty line is equal to FCFA204845, i.e., US$ 409.69 (1$=500 FCFA).

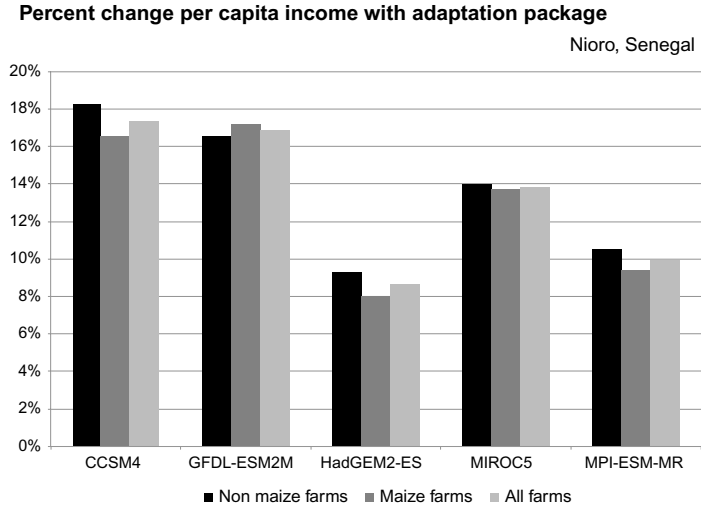


Fig. 15. Effect of climate change with adaptation on the percentage change in *per capita* income of farmers in Nioro, Senegal.

Conclusions and Next Steps

This study has shown that projected climate change as shown by the five GCMs would adversely affect the productivity of cereals in Nioro, Senegal and Navrongo, Ghana under the current production system. Simulated impacts of climate change without adaptation were severe in the Nioro and Navrongo, given that climate projections and crop yield simulations in the two areas show similar dynamics, despite slight differences in projected yield, temperature, and rainfall levels. The simulated impact of climate change was also higher with DSSAT than APSIM. The use of base technology (i.e., current crop varieties) most often resulted in lower yield under future climate scenarios.

This study has shown that farmers in Nioro du Rip, Senegal may witness varying levels of negative impacts in their net per farm revenues and *per capita* income, and increases in poverty rates under hypothesis of climate change without adaptation. Using current crop varieties in the context of projected future rainfall regimes will result in lower productivity (based on DSSAT and APSIM models), and thus lower returns.

Taking into account the RAPs, farmers may experience significant gains in their net revenues; *per capita* income and declines in poverty levels in the future even under climate change in Nioro. When we account for adaptation, as well as future increases in agricultural development, most farmers in Nioro may gain from climate

change. The adoption rate of the adaptation package reaches a minimum of 64% for Nioro on aggregate. Adaptation strategies may offset some of the negative impacts of climate change on agriculture in SSA. In some circumstances, the net impact of climate change may be positive. Thus, it is critical to design the right measures and incentives and to ensure that climate-resilient strategies are adopted. Further consultations with stakeholders will be intensified in future studies to enable them to apply the outcome of study. This will also facilitate the process of dissemination of the results. More of the adaptation packages that were identified with stakeholders will be explored in future studies.

References

Adiku, S. G. K. and Stone, R. C. (1995). Using the southern oscillation index in improving rainfall prediction and agricultural water management in Ghana, *Agric. Water Manage.*, **29**, 85–100.

Adiku, S. G. K., Jones, J. W., Kumaga, F. K., and Tonyigah, A. (2009). Effects of crop rotation and fallow residue management on maize growth, yield and soil carbon in a forest-savanna transition zone of Ghana, *J. Agric. Sci.*, **147**, 313–322.

Adiku, S. G. K., Mawunya, F. D., Jones, J. W., and Yangyuoru, M. (2007). "Can ENSO Help in Agricultural Decision Making in Ghana?", in Sivakumar, M. V. K. and Hansen, J. (eds.), *Climate Prediction and Agriculture: Advances and Challenges*, Springer-Verlag, Berlin, pp. 205–212.

Akponikpe P. B. I. (2008). *Millet response to water and soil fertility management in the Sahelian Niger: experiments and modelling*, PhD thesis, Université Catholique de Louvain, Belgium.

Akponikpe, P., Gérard, B., Michels, K., and Bielders, C. (2010). Use of the APSIM model in long term simulation to support decision making regarding nitrogen management for pearl millet in the Sahel, *Eur. J. Agron.*, **32**, 144–154.

Antle, J. M. and Stoorvogel, J. J. (2006). Predicting the Supply of Ecosystem Services from Agriculture, *Am. J. Agric. Econ.*, **88**(5), 1174–1180.

Bostick, W. M., Bado, B. V., Bationo, A., Soler, T. C., Hoogenboom, G., and Jones, J. W. (2006). Soil carbon dynamics and crop residue yields of cropping systems in the Northern Guinea Savanna of Burkina Faso, *Soil Tillage Res.*, **93**, 138–151.

Brams, E. A. (1971). Continuous cultivation of West African soils: Organic matter diminution and effects of applied lime and phosphorus, *Plant Soil*, **35**, 401–414.

Dzotsi, K., Agboh-Noameshie, A., Bontkes, T. E. S., Singh, U., and Dejean, P. (2003). "Using DSSAT to derive optimum combinations of cultivar and sowing dates for maize in Southern Togo", in Bontkes, S. and Wopereis, M. C. S. (eds.), *Decision Support Tools for Smallholder Agriculture in Sub-Saharan Africa: A Practical Guide*, International Center for Soil Fertility and Agricultural Development, Muscle Shoals, USA.

Dzotsi, K. A., Jones, J. W., Adiku, S. G. K., Naab, J. B., Singh, U., Porter, C. H., and Gijsman, A.J. (2010). Modeling soil and plant phosphorus within DSSAT, *Ecol. Model.*, **221**, 2839–2849.

Environmental Protection Agency (2001). *Initial national communication to the United Nations Framework Convention on Climate Change*, Government of the Republic of Ghana [Online], p. 172. Available at: http://unfccc.int/resource/docs/natc/ghanc1.pdf. Accessed on 23 July 2014.

Hulme, M., Doherty, R., Ngara, T., New, M., and Lister, D. (2001). African climate change: 1900–2100, *Clim. Res.*, **17**, 145–168.

IPCC (2007). *Climate Change 2007: the physical science basis*, contribution of working group I to the third assessment report of the intergovernmental panel on climate change, Cambridge University Press, Cambridge, p. 996.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT Cropping System Model, *European Journal of Agronomy*, **18**, 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., Mclean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An Overview of APSIM, a model designed for farming systems simulation, *European Journal of Agronomy*, **18**, 267–288.

MacCarthy, D. S., Sommer, R., and Vlek, P. L. G. (2009). Modeling the impacts of contrasting nutrient and residue management practices on grain yield of sorghum (Sorghum bicolor (L.) Moench) in a semi-arid region of Ghana using APSIM, *Field Crops Res*., **113**(2), 105–115.

MacCarthy, D. S., Vlek, P. L.G., Bationo, A., Tabo, R., and Fosu, M. (2010). Modeling nutrient and water productivity of sorghum in smallholder farming systems in a semi-arid region of Ghana, Field Crops Research, **118**(3), 251–258.

MacCarthy, D. S., Adiku, S. G. K., and Yangyuoru, M. (2013). Assessing the potential impact of climate change on maize production in two farming zones of Ghana using the CERES-Maize Model, *Ghana Policy Journal Special Issue: Climate Change in Ghana*, **5**, 29–42.

Mearns, L. O., Katz, R. W., and Schneider H. (1984). Extreme high temperature events: changes in their probabilities with changes in mean temperature, *J. Clim. Appl. Meteorol.*, **23**, 1601–1613.

Moriondo, M., Giannakopoulos, C., and Bindi M. (2011). Climate change impact assessment: the role of climate extremes in crop yield simulation, *Clim. Change*, **104**, 679–701.

Khouma, M., Jalloh, A., Thomas S. T., and Nelson G. C (2013). "West African agriculture and climate change: a comprehensive analysis — Senegal", in Jalloh, A., Roy-Macauley, H., Sereme, P., Zougmore., R., Thomas, T. S., and Nelson, G. C. (eds.), *West African Agriculture and Climate Change: A Comprehensive Analysis*, International Food Policy Research Institute, Washington, DC.

Naab, J. B., Singh, P., Boote, K. J., Jones, J. W., and Marfo, K.O. (2004). Using the CROPGRO-peanut model to quantify yield gaps of peanut in the Guinean savanna zone of Ghana, *Agron. J.*, **96**, 1231–1242.

Nutsukpo, D. K., Jalloh, A., Zougmore, R., Nelson, G. C., and Thomas, T. S. (2013). "West African agriculture and climate change: a comprehensive analysis — Ghana", in Jalloh, A., Roy-Macauley, H., Sereme, P., Zougmore., R., Thomas, T. S., and Nelson, G. C. (eds.), *West African Agriculture and Climate Change: A Comprehensive Analysis*, International Food Policy Research Institute, Washington, DC.

Rosenzweig, C., Jones, J. W., Hatfield, J., Antle, J., Ruane, A., Boote, K., Thorburn, P., Valdivia, R., Porter, C., Janssen, S., and Mutter, C. (2013). *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.0*, AgMIP, New York.

Singh, P., Nedumaran, S., Ntare, B. R., Boote, K. J. Singh, N. P., Srinivas, K., and Bantilan, M. C. S. (2013). Potential benefits of drought and heat tolerance in groundnut for adaptation to climate change in India and West Africa, *Mitigation Adaptation Strategies for Global Change*., **19**(5), 509–529.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol*., 200. doi: 10.1016/j.agr.formet.2014.09.016.

Traore, P. S. C., Kouressy, M., Vaksmann, M., Tabo, R., Maikano, I, Traore, S. B., and Cooper, P. (2007). "Climate Prediction and Agriculture: What is different abut Sudano-Sahelian West Africa", in

Sivakumar, M. V. K. and Hansen, J. (eds.), *Climate Prediction and Agriculture: Advances and Challenges*, Springer-Verlag, Berlin, pp. 189–203.

Yaye, H., Danguioua, A., Jalloh, A., Zougmore, R., Nelson, G. C., and Thomas, T. S. (2013). "Niger Faso: West African agriculture and climate change: a comprehensive analysis — Ghana", in Jalloh, A., Roy-Macauley, H., Sereme, P., Zougmore., R., Thomas, T. S., and Nelson, G. C. (eds.). *West African Agriculture and Climate Change: A Comprehensive Analysis*, International Food Policy Research Institute, Washington, DC, pp. 233–258.

This page intentionally left blank

Chapter 3

Impacts of Climate Variability and Change on Agricultural Systems in East Africa

Karuturi P. C. Rao[1], Gummadi Sridhar[1], Richard M. Mulwa[2], Mary N. Kilavi[3], Anthony Esilaba[4], Ioannis N. Athanasiadis[5], and Roberto O. Valdivia[6]

[1]*International Crops Research Institute for the Semi-Arid Tropics, Addis Ababa, Ethiopia*

[2]*University of Nairobi, Nairobi, Kenya*

[3]*Kenya Meteorological Department, Nairobi, Kenya*

[4]*Kenya Agricultural Research Institute, Nairobi, Kenya*

[5]*Democritus University of Thrace, Xanthi, Greece*

[6]*Oregon State University, Corvallis, OR, USA*

Introduction

With growing evidence and increasing awareness that the climate is changing and will continue to change even under reduced greenhouse gas emissions (IPCC, 2013), the focus now shifts to understanding the impacts of the projected changes and to developing strategies that help in adapting to the same. However, adaptation planning requires accurate information about where, when, and how the impacts will be felt and who will be more vulnerable. Agriculture, especially as practiced under rainfed conditions, is one of the most vulnerable sectors to climate variability and change because they are important determinants of its productivity. Among the regions, Africa is considered more vulnerable due to its high dependence on agriculture for subsistence, employment, and income.

In East Africa, agriculture provides 43% of GDP and contributes to more than 80% of employment (Omano *et al.*, 2006). East Africa suffers from both periodically excessive and deficient rainfall (Hastenrath *et al.*, 2007; Webster *et al.*, 1999). Generally the region experiences prolonged and highly destructive droughts that cover large areas at least once every decade and more localized events occur more frequently. Based on the analysis of data from the International Disaster Database (EM-DAT), Shongwe *et al.* (2009) report that there has been an increase in the

number of reported disasters in the region; from an average of less than three events per year in the 1980s to over seven events per year in the 1990s and ten events per year from 2000–2006.

The negative impacts of climate are not limited to the years with extreme climatic conditions. Even with normal rainfall, the countries in the region do not produce enough food to meet their needs and many them are net importers of food. Overlaid on this challenging scenario is the dominance of semi-arid to arid climatic conditions, degraded soils, extreme poverty, and lack of infrastructure, which make these countries highly vulnerable to future changes in climate (Fischer *et al.*, 2005; IPCC, 20013).

There is a rapidly growing literature on vulnerability and adaptation to increased climatic variability and climate change, but most of these assessments are based on statistical and empirical models that fail to account for the full range of complex interactions and their effects on agricultural systems (Cline, 2007; Lobell *et al.*, 2008; Parry *et al.*, 2004). For developing and implementing adaptation programs, more detailed information about the components of the prevailing systems (such as which crops and varieties are more vulnerable and which management practices are not viable under the predicted climates) is needed. Several problems hinder such an assessment. First, there is the lack of availability of downscaled local-level climate change projections. While climate models provide various scenarios with higher levels of confidence at global and subregional levels, uncertainty prevails over the exact nature of these changes at local levels (IPCC, 2007). Second, information is lacking on how the projected changes in climate impact agricultural systems, especially smallholder agriculture. Though process-based crop simulation models can serve as tools to capture these interactions and make more realistic assessments of climate effects on agricultural systems, application is often limited to a few location-specific studies mainly because of the intensive data requirements and practical limitations, including the capacity to calibrate, validate, and perform detailed analyses. Third, there is scarcity of information on how the impacts of climate change on the production and productivity of agriculture translate into economic impacts, including food security at household and national levels.

This assessment is aimed at developing more accurate information on how projected changes in climate might affect smallholder farmers through impacts on productivity and profitability of agricultural systems that are widely adopted in East Africa, by using protocols and methods developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013a). The assessment is designed to capture the complexity and diversity that exist in the smallholder farming systems, including the different ways in which the system is managed (Fig. 1). AgMIP has developed methods and protocols that integrate state-of-the-art downscaled climate scenarios, by using crop and economic models (Rosenzweig

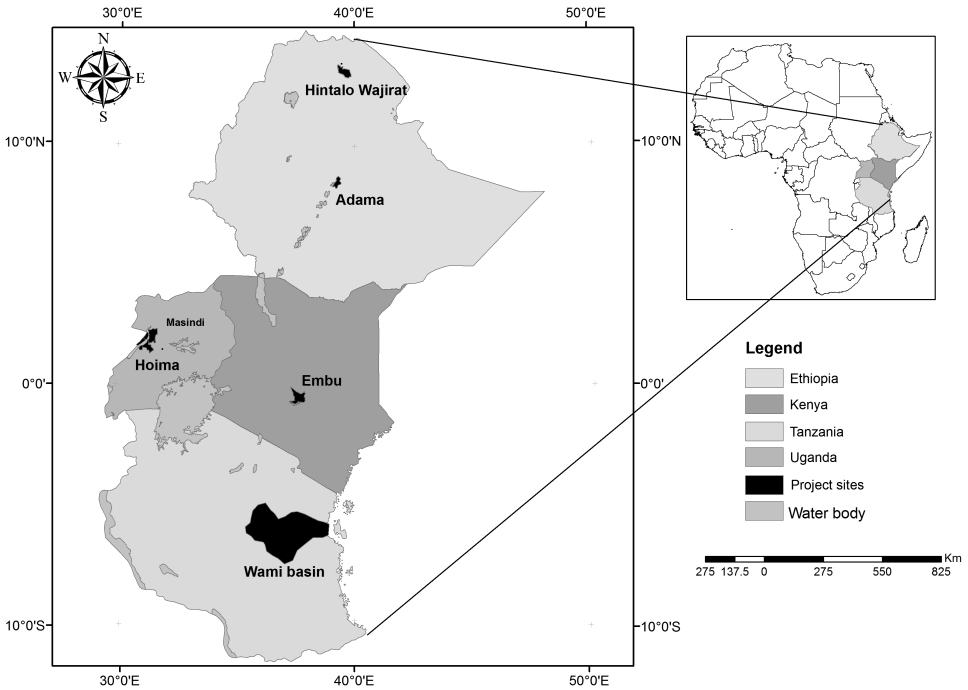


Fig. 1. AgMIP study areas in Eastern Africa.

et al., 2013b). This paper examines the results from the integrated assessment carried out on smallholder farming systems in different agroecological zones (AEZs) of Embu County in Kenya and explores their possible impacts on income, poverty, and food security. It also discusses some of the available options that can be used to mitigate the negative impacts effectively while capitalizing on the opportunities created.

Farming System Investigated

Settings and locations

Embu County in Kenya, which lies on the southeast slopes of Mount Kenya, covers the typical agroecological profile of the region, from cold and wet high-altitude areas to the hot and dry low-altitude areas (Fig. 2). The region is bounded by latitude 0°53'S and longitude 37°45'E. The county slopes from west to east (Jaetzold *et al.*, 2007). According to the 2009 population census, the district had a total population of 543,221 people with an annual growth rate of 1.7%. The National Report on Poverty in Kenya 2000 indicated that 56%of the population in Embu District is absolutely poor while 43.5% of them were categorized as chronically poor. Absolute poverty is a

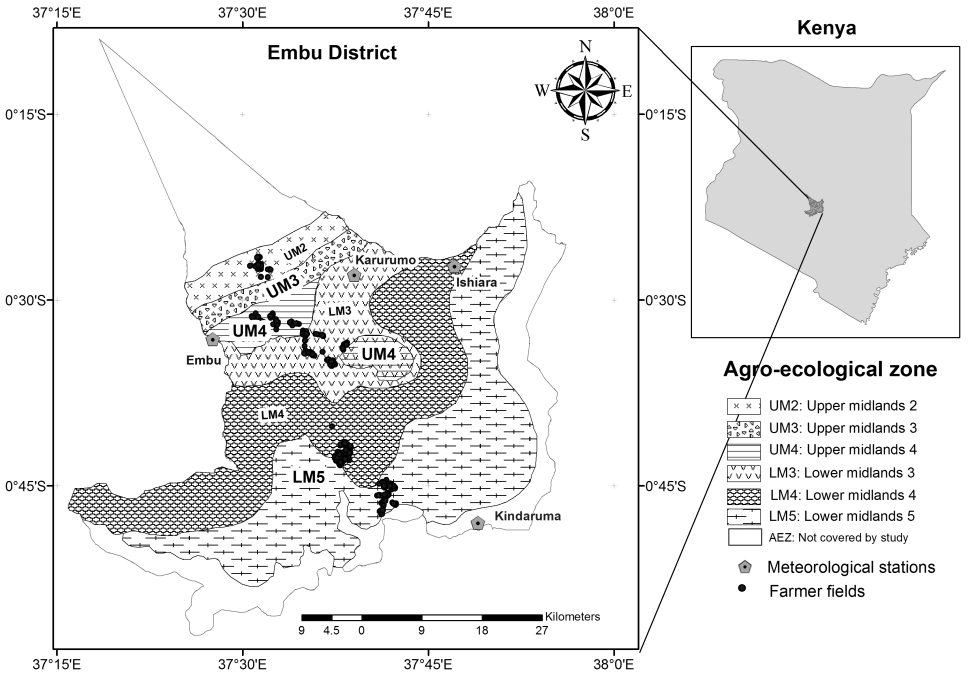


Fig. 2. Target AEZs in Embu County (based on Jaetzold *et al.*, 2007).

condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education, and information (UN, 1995). Chronic poverty is a condition whereby an individual or group is in a state of poverty over an extended period of time (Aaberge and Mogstad, 2007).

Agriculture in the county is predominantly rainfed and highly dependent on seasonal rainfall patterns. The seasonality is associated with the annual migration northwards and southwards of the Intertropical Convergence Zone (ITCZ) (Griffiths, 1972; Jackson, 1989; Osei and Aryeetey-Attoh, 1997), which is located over the equator in March to April and again in October to November. Consequently, the areas nearest to the equator, such as parts of Kenya and Tanzania, experience two distinct rainfall seasons during the year. Away from the equator, in south Tanzania and north Ethiopia, there is only one rainy season. Agricultural systems in the region have evolved along these climatic patterns. The average rainfall in the county varies from more than 2200 mm at an altitude of 2500 m to less than 600 mm near the Tana River at 700 m. The average temperatures vary from 28.8°C in the hottest month to 9.6°C in the coldest month (Jaetzold *et al.*, 2007).

The county is divided into 11 AEZs based on the probability of their meeting the temperature and water requirements of the main crops grown (Table 1). The upper highlands (UH0) and lower highlands (LH0) are so wet and steep that forest

Table 1. AEZs of Embu County and climate of the zones (Jaetzold *et al.*, 2007).

AEZ		Altitude (m)	Annual mean temperature (°C)	Annual rainfall (mm)
UH0	Upper highland forest zone	>2500	NA	NA
LH0	Lower highland forest zone	>2500	NA	NA
LH1	Lower highland tea–dairy zone	1900–2100	17.7–15.8	1750–2000
UM1	Upper midland coffee–tea zone	1600–1850	18.9–17.5	1400–1800
UM2	Upper midland main coffee zone	1400–1600	20.1–18.9	1250–1500
UM3	Upper midland marginal coffee zone	1280–1460	20.7–19.6	1000–1250
UM4	Upper midland sunflower–maize zone	1200–1400	20.9–20-0	980–1100
LM3	Lower midland cotton zone	1070–1280	22.0–21.0	900–1100
LM4	Lower midland marginal cotton zone	980–1220	22.5–21.0	800–900
LM5	Lower midland livestock–millet zone	830–1130	23.9–21.7	700–800
IL5	Inner lowland livestock–millet zone	600–850	25.4–24.0	500–710

is the best land use. In the lower highlands zone (LH1) and upper midland zone (UM1), precipitation is 1800 mm or more and average annual temperatures are less than 18°C. The predominant cropping systems there are tea- and coffee-based. The contribution of these AEZs, along with the relatively small inner lowland (IL5) zone, to food production in the county is fairly small. The remaining seven zones, ranging from the upper midland main coffee zone (UM2) to the lower midland livestock–millet zone (LM5), are the main cropping areas. The rainfall during the main crop growing period declines rapidly from UM2 to LM5.

Soil and climate data

Long-term historical climate data for several locations in Embu County for the baseline period 1980–2010 were collected from the archives of the Kenya Meteorological Department (KMD) to characterize variability in the observed climate, develop future scenarios, and to use with the crop simulation models, DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems Simulator) (IBSNAT, 1989; McCown *et al.*, 1996). Though the minimum data requirement includes daily records of rainfall, minimum and maximum air temperatures, and solar radiation, the KMD has only one synoptic station located at the Embu Research Farm of the Kenya Agricultural Research Institute (KARI) where data on all the required parameters are collected. At all other stations in the county, only rainfall measurements are taken, and for many of these locations, available data are incomplete. From the available data, four stations for which good-quality data (with less than 10% missing records) are available were selected. These include the synoptic station Embu for AEZs UM2 and UM3 and rainfall stations Karurumo for LM3, Ishiara for LM4, and Kindaruma for LM5. Historical climate

Table 2. Key climate characteristics of the selected AEZs in Embu County.

Variable	AEZ			
	UM2 and UM3	LM3	LM4	LM5
Average rainfall (mm)				
Annual	1248 (26)	1141 (24)	823 (25)	833 (29)
LR season	583 (35)	471 (25)	327 (26)	331 (33)
SR season	490 (39)	565 (37)	431 (37)	407 (43)
Average temperature (°C)				
Annual mean	19.4	19.1	21.2	22.4
Annual maximum	24.5	24.3	26.9	28.1
Annual minimum	14.2	13.8	15.5	16.7
LR season mean	20.5	20.3	22.5	23.8
LR season maximum	25.6	25.6	28.3	29.5
LR season minimum	15.4	15.0	16.7	18.0
SR season mean	19.6	18.9	20.8	22.3
SR season maximum	24.7	24.0	26.4	27.8
SR season minimum	14.4	13.7	15.3	16.7

Note: Figures in parentheses represent coefficient of variation (CV).

data were subjected to quality control by using R-Climdex (Zhang and Feng, 2004), which flagged out the spurious values. Bias-corrected AgMERRA (Ruane *et al.*, 2014) datasets were used to fill the missing values and to replace the spurious ones. The bias correction was achieved by calculating a correction factor between each variable of the MERRA data and the corresponding observations for every month and employing the factor on the MERRA data to estimate the missing values. For the three locations, Ishiara, Karurumo, and Kindaruma (for which only precipitation data is available) other variables were all estimated from the MERRA data by using correction factors for the Embu station.

The Embu and Karurumo sites, which receive more than 1000 mm rainfall annually, are generally considered as high-potential areas, while the Ishiara and Kindaruma sites (with about 800 mm rainfall annually) are considered as medium-to-low potential areas for maize production (Table 2). Rainfall in the region is bi-modal with two distinct rainy seasons, which are locally referred to as the short rains (SR) season from October to December and the long rains (LR) season from March to May.

In general, the SR season receives more rain than the LR season. This is true for all the selected sites except Embu, where rainfall during the LR season is 19% higher than that during the SR season. Rainfall at all sites showed high temporal variability, with a coefficient of variation greater than 25%. Annual rainfall at Embu and Kindaruma sites showed higher variability than that at Ishiara and Karurumo.

At all sites, variability in rainfall during the SR season is higher than that during the LR season. Embu, with an altitude of about 1500 m above mean sea level, is the coolest of the four sites used in this assessment. Temperatures during the LR season are higher compared to the SR season at all sites. The county experiences higher temperatures during the period February to April and lower temperatures during July to September.

The main source of soil data is reports of the Soil Survey Division of KARI. The county is mostly covered by four distinct soil types (Fig. 3) and one representative soil profile for each soil type was selected for use with the DSSAT and APSIM crop models. The first group of soils (RB1, RB2, and RB3) is a well-drained, extremely deep, reddish brown to dark brown, friable and slightly smeary clay, with acid

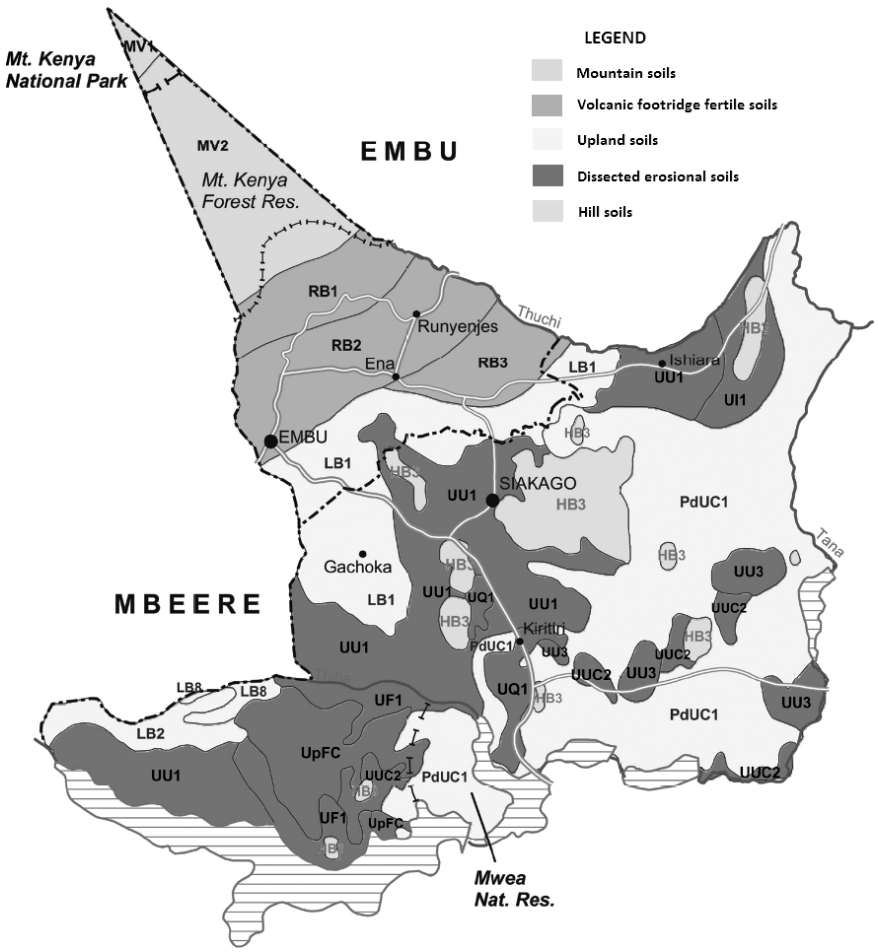


Fig. 3. Distribution of soil types in Embu County (Jaetzold *et al.*, 2007).

Table 3. Properties of soil profiles representing AEZs in Embu County.

Soil Properties	Embu	Kavutiri	Gachuka	Machanga
Target AEZ	UM2	UM3 and LM3	LM4	LM5
Soil type	Typic Palehumult	Othoxic Palehumult	Typic Haplorthox	
Soil layers/depth (cm)	4/102	6/200	4/104	4/80
Sand, silt, clay (percentage in 0–15 cm)	20, 24, 56	20, 26, 54	20, 24, 56	—
Plant available water	93.7	152.2	89.4	100
Organic matter (top three layers)	2.09, 1.49, 0.91	3.61, 2.29, 1.58	2.29, 1.58, 0.92	0.58, 0.5, 0.4

humic topsoil. The soil profile selected to represent this type is Kavutiri. The area demarcated on the map as LB1 is represented by the Embu soil profile, which is a well-drained, very deep, dark red, very friable clay soil. The third soil profile Gachuka represents the area demarcated on the map as PdUC1, which is a complex of well-drained, shallow, dark red to yellowish red, friable to firm, stony, loamy sand to clay soils. The fourth profile, Machanga, covers the region marked on the map as UU. The soils in this area are well-drained, shallow to deep, dark red to yellowish brown, loose loamy sand to friable sandy clay loam with rocky and stony inclusions. These soil types are generally classified as entisols and oxisols.

The profile description taken from the soil survey reports is considered to represent average soil conditions in the study area. Considering the high variability in soil conditions across the farms and the need to account for the same, for each of the soil profiles selected three variants (good, average, and poor) were created by increasing or decreasing the soil organic matter and plant available water contents by 20%. With these variants, a total of 12 soil profiles were created, and a summary of the key characteristics of the profiles under the category "good" is presented in Table 3. These profiles are assigned to individual farms, based on the location of the farm and the perception of the farmer about the fertility status of his farm as captured in the survey. During the survey, farmers were asked to rate the fertility status of their farm as "good", "average", or "poor" when compared to general conditions in the farms of that area.

Farming systems

The most common farming systems in the county are small-scale cash-crop and subsistence farming (Fig. 4). The cropping patterns are determined by the district

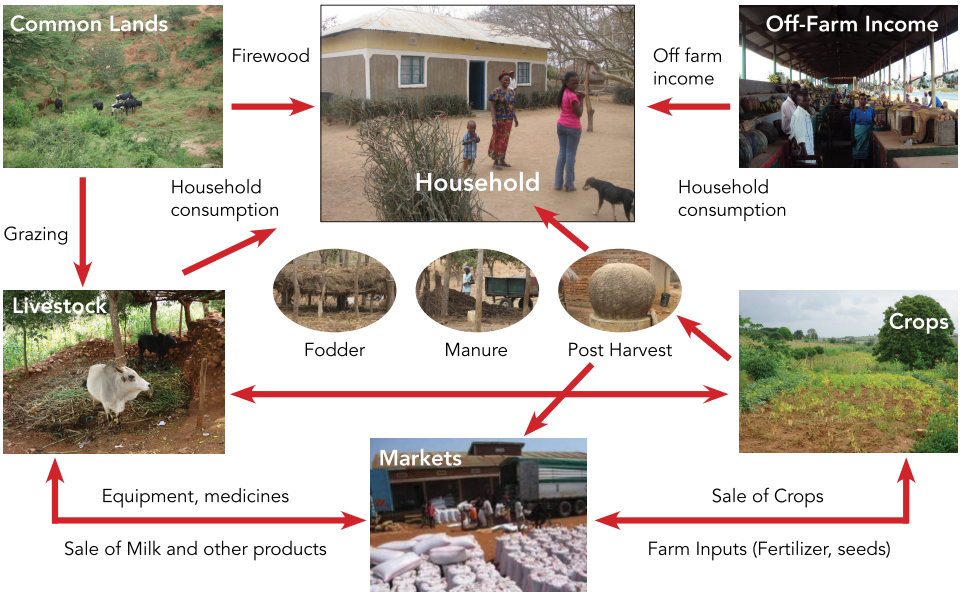


Fig. 4. Typical East African farming system showing main components of the system and their relationships.

Table 4. Characteristics of smallholder farms in AEZs of Embu County.

AEZ	Mean household size	Mean farm size (ha)	Mean dairy herd size	Fertilizer use (kg N/ha)	Dominant maize variety	Average maize yields (kg/ha)
UM2	4.3	0.91	2.29	12.1	DK41, H513	1030
UM3	5.7	2.21	1.79	15.0	Duma, H513	1195
LM3	5.8	1.85	1.83	12.8	Duma, DK43, Katumani,	1021
LM4	6.5	2.43	2.2	9.4	Katumani, Duma, DK43	960
LM5	6.9	1.74	1.88	4.1	Katumani, Duma	525

AEZs. The intensity of land use decreases from upper midland zones to lower midland zones. Some important characteristics of the farming systems in the target AEZ areas are shown in Table 4.

Agriculture in the selected AEZs is characterized by extreme dependence on rainfall. The amount and fluctuations in the temporal distribution of rainfall and surface temperature are the most important determinants of interannual variability in crop production. Farmers practice low-input agriculture that is low in productivity mainly due to the risk associated with erratic and unreliable rainfall during and between the seasons. A mixed crop–livestock system is the most widespread practice.

In UM2, UM3, and UM4, key crops are maize and beans, but farmers also grow coffee as a cash crop. In addition, they also plant bananas, vegetables, and sweet potatoes. Crops grown by farmers in LM3 are similar to those grown in UM2 and UM3 except coffee. Some farmers in this AEZ grow sorghum and millet on small areas. Farmers in LM4 and LM5 plant pigeon peas in addition to other crops grown in LM3. Though farmers in all AEZs grow maize, there are significant differences in the variety grown and in the management employed. Farmers in the high-potential UM2, UM3 and LM3 areas use long-duration high-yielding varieties, while those in the low-potential LM4 and LM5 areas favor short-duration varieties as a drought-escaping strategy. In general, use of fertilizer is very low and the number of farmers using fertilizer, especially in agroecologies LM4 and LM5, is very limited. The areas occupied by various crops also vary from farm to farm and from season to season.

Stakeholder Interactions, Meetings, and Representative Agricultural Pathways

Currently, besides growing maize, farmers in different AEZs of Embu County are involved in various other farming activities. These systems are dynamic and hence there is the need for representative agricultural pathways (RAPs) to predict potential future scenarios both at farm level and also at the household level. The impacts of climate change and vulnerability of the communities are long term in nature and depend on socio-economic developments and on how these developments shape the future agricultural systems. RAPs were developed to project the current production system into the future. RAPs are combinations of economic, technology, and policy scenarios that represent a plausible range of possible futures. They are qualitative storylines that can be translated into model parameters such as farm and household size, prices and costs of production, and policy. To this end, discussions were held with representatives from different government and non-governmental agencies and other organizations about current and future trends in agriculture and other socio-economic developments to map future agricultural systems. The RAPs meeting was held at the World Agroforestry Centre offices in Nairobi in June 2013, and it attracted 16 participants from government agencies, universities, CGIAR organizations, and the local research organization.

In development of the RAPs, we presented the stakeholders with two scenarios; an optimistic one and a pessimistic one as discussed by Claessens *et al.* (2012). In the optimistic one, it is assumed that Kenya follows a more positive economic development trajectory than in the past 30 years, with higher rates of economic growth, movement of labor out of agriculture into other sectors, reductions in rural household size, and increases in farm size. In addition, investments in transportation and communication infrastructure are expected to increase, and more open trade and

liberalized domestic policies will be adopted. This scenario also assumes higher real prices for traded agricultural commodities such as maize and also policy changes and infrastructure improvements, which will lead to lower real prices of critical agricultural inputs such as mineral fertilizer and improved seeds.

The pessimistic scenario assumes that Kenya will continue experiencing a low rate of economic growth; population growth rates will remain high, rural populations will increase, farm sizes will decline, and rural household sizes increase. In addition, transportation infrastructure will deteriorate, and the government will adopt trade policies that discourage exports so that prices to farmers remain at current levels. Taxes on imports of critical inputs such as fertilizers are expected to increase and soil fertility and agricultural productivity will continue to decline to an even lower level equilibrium than was observed in the early part of the 21st century.

Given the two projected development paths, the stakeholders agreed to work with the business-as-usual scenario, which was mostly reflected by the optimistic scenario. After identifying the projected development path, stakeholders were presented with a matrix of different bio-physical, socio-economic, institutional, and technological indicators that were expected to change in the future. Discussions were then held on the directions and magnitudes of the different indicators and why they believed this was going to be the case. For some indicators, stakeholders would readily agree, while for others such as change in farm sizes, there were split opinions both on the magnitude and direction.

Data and Methods of Study

The assessment used AEZs representing unique combinations of climatic and soil conditions that are homogeneous with regard to their capacity to support production of a wide range of food and cash crops as the unit for evaluating the impacts of climate variability and change. Relevant data required to calibrate, validate, and apply climate, crop, and economic models for each of the seven target AEZs was collected from various secondary sources which include informal publications such as research reports.

Since data on several parameters required by the crop and economic models are not readily available, a survey was done in Embu County to characterize the smallholder nfarming systems in the target AEZs. The information collected included various enterprises that the farmers are involved with, their management and productivity, as well as sources of non-farm income to the households. The methodology used for data collection was a combination of stratified and multi-stage sampling. The strata for the survey were the selected AEZs, which include UM2, UM3, LM3, LM4, and LM5. At each AEZ, administrative regions were chosen (division, location, and sublocation) and one sublocation representing each AEZ was chosen for

Table 5. Distribution of sampled households by AEZ in Embu County.

AEZ	Division	Number of households
UM2	Kevote, Nembure	81
UM3	Kithimu, Nembure	89
LM3	Riandu, Siakago	107
LM4	Nyangwa, Gachoka	92
LM5	Mavuria, Gachoka	84

sampling. At the sublocation level, data collection was by simple random sampling. The sublocations chosen for sampling were Kevote in UM2, Kithimu in UM3, Riandu in LM3, Nyangwa in LM4, and Mavuria in LM5. A total of 453 households were sampled, as shown in Table 5.

Climate

Observed trends in temperature and precipitation

A clear increasing trend in the maximum and minimum temperatures was observed since 1990 (Fig. 5). Though both maximum and minimum temperatures have increased, the increase in maximum temperatures is higher than that in minimum temperatures. The average annual maximum temperatures during the period 2001–2010 were 0.54°C higher than the temperatures recorded during the period 1980–1989, while the corresponding increase in minimum temperature was 0.30°C. Differences were also observed between the two rainy seasons with higher

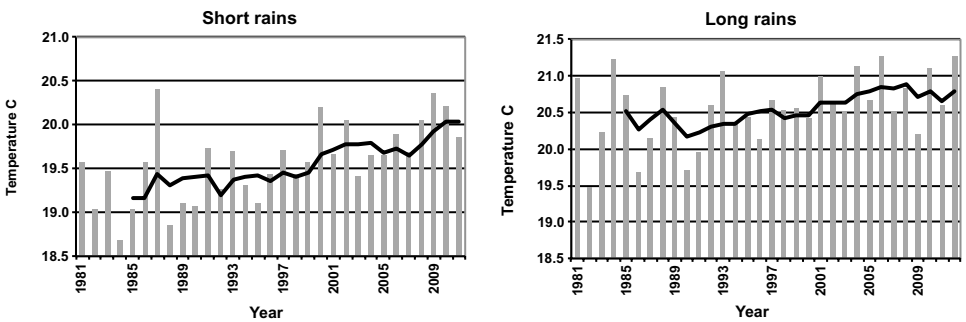


Fig. 5. Variability and trends in average air temperature during short and long rain seasons in Embu County during the period 1980–2010.

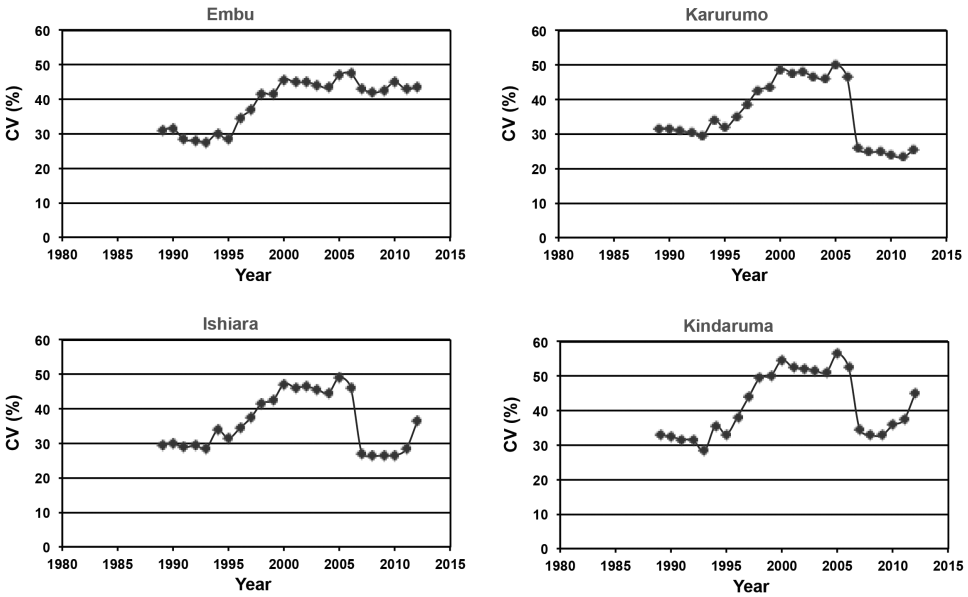


Fig. 6. Ten-year moving coefficient of variation (CV) of rainfall starting from 1980 during SR season at four sites in Embu County.

increase during the SR season in both minimum and maximum temperatures. The average annual temperatures in 2001–2010 were higher by 0.57°C during the SR season and by 0.49°C during the LR season, compared to the 1980–1989 period.

While no clear trend was observed in the amount of rainfall received annually or seasonally during the baseline period from 1980–2010, there are indications that variability in rainfall, as indicated by the trends in the ten-year moving coefficient variation (CV), is increasing during the SR season and decreasing in the LR season (Fig. 6). This is a significant change, since the SR season is the period in which the main food crop (i.e., maize) is grown and is generally considered as more reliable in the region.

The Mann–Kendall tau-b non-parametric function that computes a coefficient representing strength and direction of trend in equally spaced data was used to test the significance of the observed trends in temperature and rainfall (Table 6). The p values from the test indicate that the trends in temperature are significant at less than 0.02; trends in rainfall are less conclusive due to strong interannual and interdecadal variability.

Table 6. Kendall tau significance test for annual and seasonal precipitation and temperature at different locations in Embu County.

		Temperature	Precipitation			
		EMBU	Embu	Ishiara	Karurumo	Kindaruma
Annual	Kendall's tau	0.43	0.22	0.34	0.12	0.38
	p-value	0.00	0.13	0.02	0.45	0.01
SR season	Kendall's tau	0.30	0.26	0.14	0.14	−0.05
	p-value	0.02	0.08	0.36	0.34	0.75
LR season	Kendall's tau	0.35	0.52	0.10	−0.03	0.29
	p-value	0.01	0.00	0.51	0.86	0.05

Climate projections

Since it is not practical to assess impacts of climate change on agricultural systems at the local scale with coarse data from coupled atmosphere–ocean general circulation models (AOGCMs), location-specific climate change scenarios were developed by using a simple delta method in which monthly changes in temperature and precipitation from an AOGCM, calculated on the grid scale, are added to the corresponding observed station data. The delta method assumes that future model biases for both mean and variability will be the same as those in present day simulations (Wilby *et al.*, 2004). Climate change scenarios for mid-century (2041–2070) and end-century (2071–2100) periods were developed for 20 AOGCMS from the Coupled Model Intercomparison Project phase 5 (CMIP5) for two representative concentration pathways (RCPs) 4.5 and 8.5 (Moss *et al.*, 2010; Taylor *et al.*, 2012).

Downscaled CMIP5 projected climate change scenarios showed a general increase in surface temperatures and precipitation for the four locations in Embu County (Fig. 7). However, magnitude of this increase varied over different time-periods and RCPs. Projections by using HadGEM2-CC, HadGEM2-ES, and MIROC-ESM showed higher increase in maximum temperatures, while those from CanESM2, INMCM4, MRI-CGCM3, and NorESM1-M showed very marginal increase. The highest increase in annually average maximum temperature across all scenarios was 4.8°C. Projected minimum surface temperature is also increasing but the increase in minimum temperature is projected to be higher than that in maximum temperature. The BNU-ESM, GFDL-ESM2G, GFDL-ESM2M, and NorESM1-M climate models showed only a marginal increase in temperatures. The maximum increase in minimum temperature is 5.8°C (Fig. 7).

The GFDL-ESM2G, HadGEM2-CC, HadGEM2-ES, MIROC5, and NorESM1-M GCMs project declines in annual rainfall from –0.5% to –25%, while the

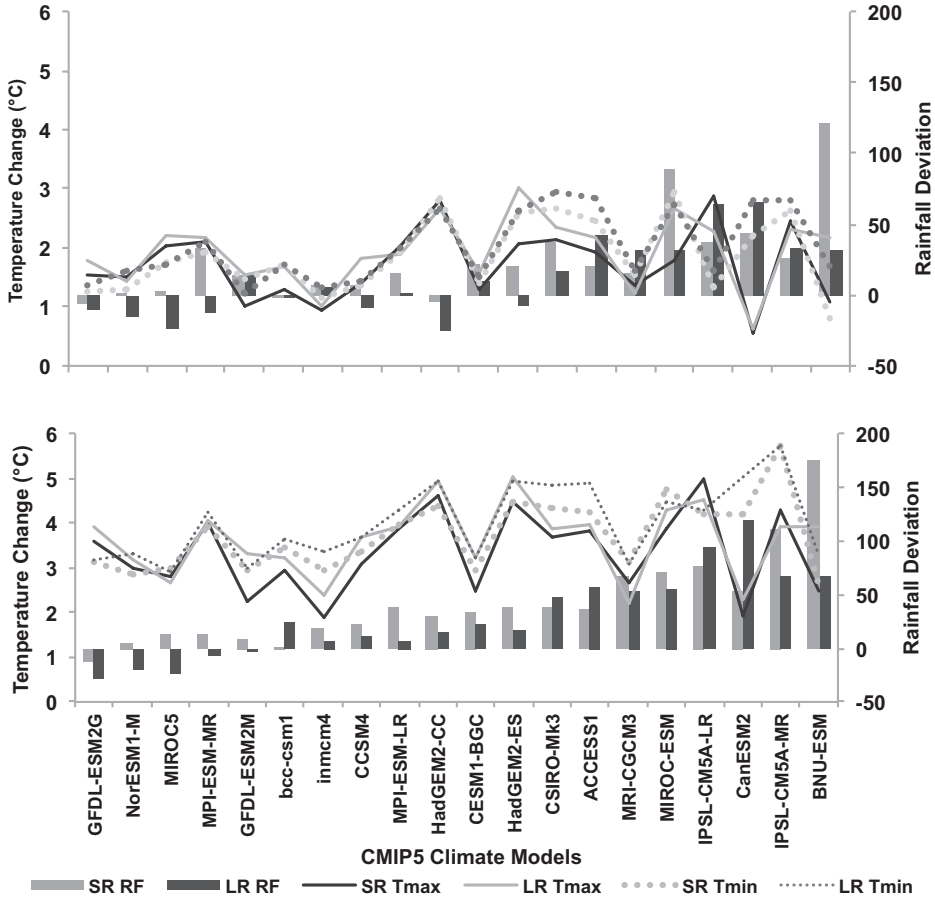


Fig. 7. Projected changes in rainfall (percent deviation from historic rainfall) and temperatures (absolute change) under RCP4.5 and8.5 to mid-century in Embu County (RF=rainfall, SR=short rains, LR=long rains, Tmax=maximum temperature and Tmin=minimum temperature)

other GCMs projected an increase across RCPs and time-periods. The BNU-ESM projected the highest increase in precipitation compared to the other GCMs. Precipitation increases considerably in RCP8.5 compared to RCP4.5.

Projected changes in mean surface temperatures and precipitation for individual months and crop seasons were also investigated. Future projected changes in mean surface temperature and precipitation records for five GCMs (CCSM4, HadGEM2ES, MIROC5, MPI ESM, and GFDL) were anyzed at monthly and seasonal intervals for two RCPs and time-periods as depicted in Fig. 8 for end-century period. In both scenarios the increase in temperature and precipitation is expected to be high during LR season (MAM).

Crops

Crop management parameters used in setting up crop model simulations for individual farms were derived from the results of the survey conducted in the target AEZs. The survey captured, among other things, variety used, date planted, and amount of seed, fertilizer, and manure applied during the 2012 LR and SR seasons, and harvested yields. Farmers in the region used a large number of varieties. The varieties mentioned by farmers during the survey included Local, DK41, DK43, H513, H613, Duma, and Pioneer. In setting parameters for these varieties, we have identified and used an equivalent variety for which data are available to derive model parameters. The identification of the equivalent variety is based on the duration and yield potential of that variety. Table 7 presents the farmer-used variety and its equivalent use in the crop model simulations. Katumani is used as the local variety.

Plant population estimates for individual farms were set based on the amount of seed used by farmers. Previous studies on farmer fields by KARI-Embu have reported that the plant population normally used by farmers varied from 30,000 plants/ha to 50,000 plants/ha. Accordingly, a plant population of 30,000 plants/ha was assigned to farmers using seed rates lower than 15 kg/ha, 40,000 plants/ha for those using 15–20 kg/ha, and 50,000 plants/ha for those using more than 20 kg/ha. The distribution of farmers in these three groups is presented in Table 8. The majority of the farmers were found to be using 30,000 plants/ha. Only 5% of the sampled farmers are in the category of sowing 50,000 plants/ha.

Survey results indicated large differences in the amount of fertilizer used by farmers in different AEZs (Table 9). Similar differences were also observed in the use of manure. While setting up the crop models for individual farms, we used the actual amounts applied by the farmers. The type of fertilizer used by farmers is mainly ammonical (calcium ammonium nitrate, di-ammonium phosphate, and NPK complex). A uniform depth of 5 cm was used for placing the fertilizer, and the entire amount was applied once, at the time of sowing.

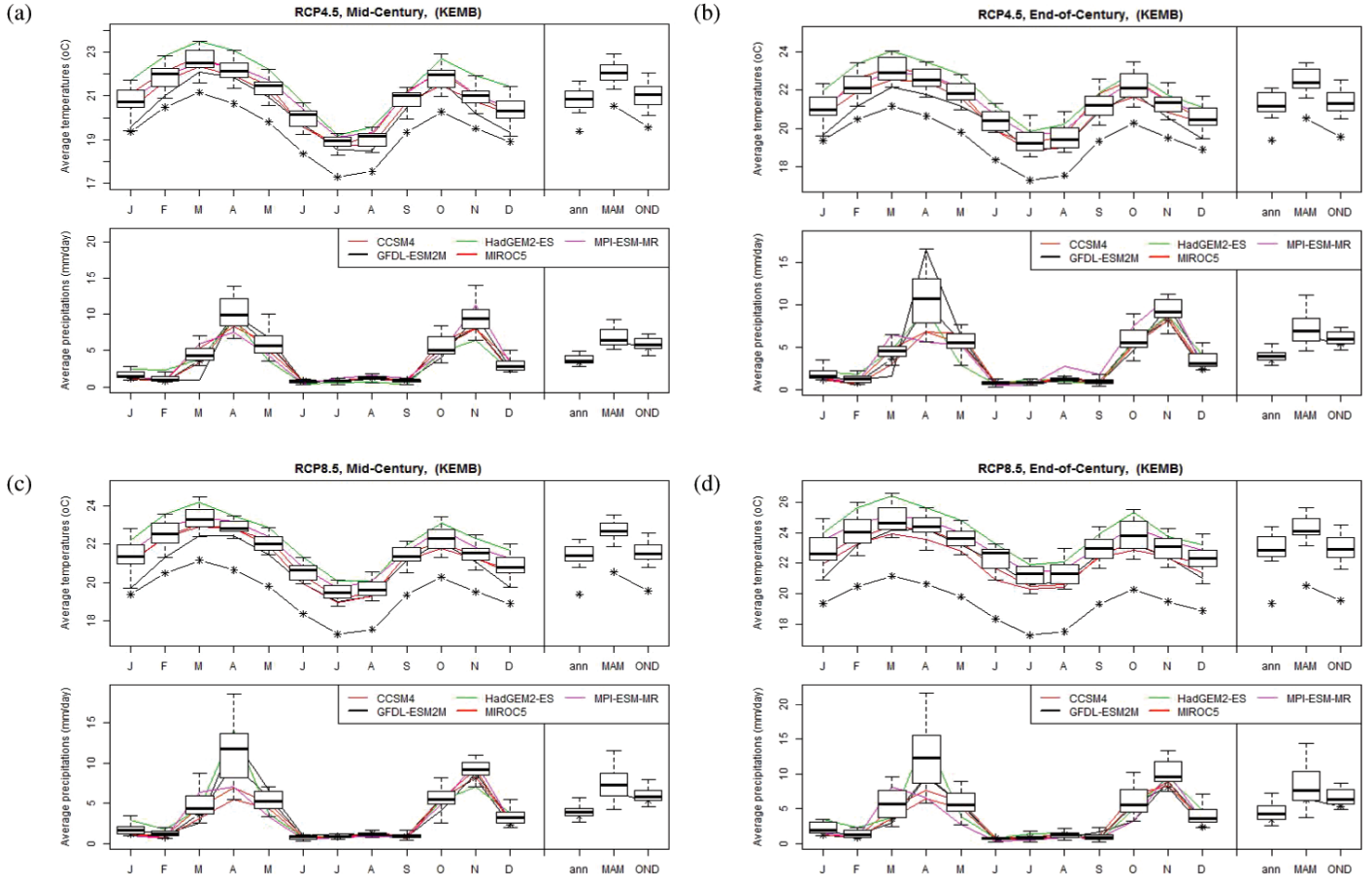


Fig. 8. Projected changes in monthly, seasonal, and annual temperature and precipitation (a) 4.5 mid-century (2014–2070), (b) 4.5 end-century (2071–2100), (c) 8.5 mid-century (2041–2070), (d) 8.5 end-century (2071–2100) at Embu in Kenya.

Table 7. Maize varieties used by farmers in different AEZs in Embu County and their corresponding equivalent cultivar in the model.

Variety used by farmer	Duration (months)	Yields (t/ha)	Variety in crop models used
DK41		5–6	Deka_lb
DK43		6–7	H511
H513	4–5	6–8	H511
H613	6–8	8–10	H513
Local	All		Katumani
Duma	4–5	6–7	H511
Pioneer	5–6	8–10	H513
Others	Considered as local		Katumani

Table 8. Number of farmers using different levels of plant population in different AEZs of Embu County.

Plant population (plants/ha)	UM2	UM3	LM3	LM4	LM5	Total
30,000	31	55	50	69	63	268
40,000	39	27	48	18	18	150
50,000	3	5	8	4	1	21

Table 9. Number of farmers under different levels of fertilizer use (kg/ha) in the five different AEZs of Embu County.

Fertilizer (kg/ha)	UM2	UM3	LM3	LM4	LM5	Total
<10	10	7	16	20	47	100
10–25	25	12	14	27	24	102
25–50	30	24	32	43	25	154
>50	21	38	34	19	5	117

Crop model calibration (*DSSAT and APSIM*)

The maize varieties H511, H513, Dekalb, and Katumani were selected to represent the varieties used by farmers in the county. DSSAT and APSIM were calibrated for these maize varieties using the unpublished data from a study conducted on the research farm of the KARI-Embu research station. The trial was conducted during the period 2000–2002 over three seasons (SR season of 2000 and SR and LR seasons of 2001) and tested three varieties, *viz.*, H511, H513, and Katumani. Available data included dates of sowing, days to tasseling and flowering, days to maturity, and grain and dry matter yields, at harvest and also during the crop growing periods. For

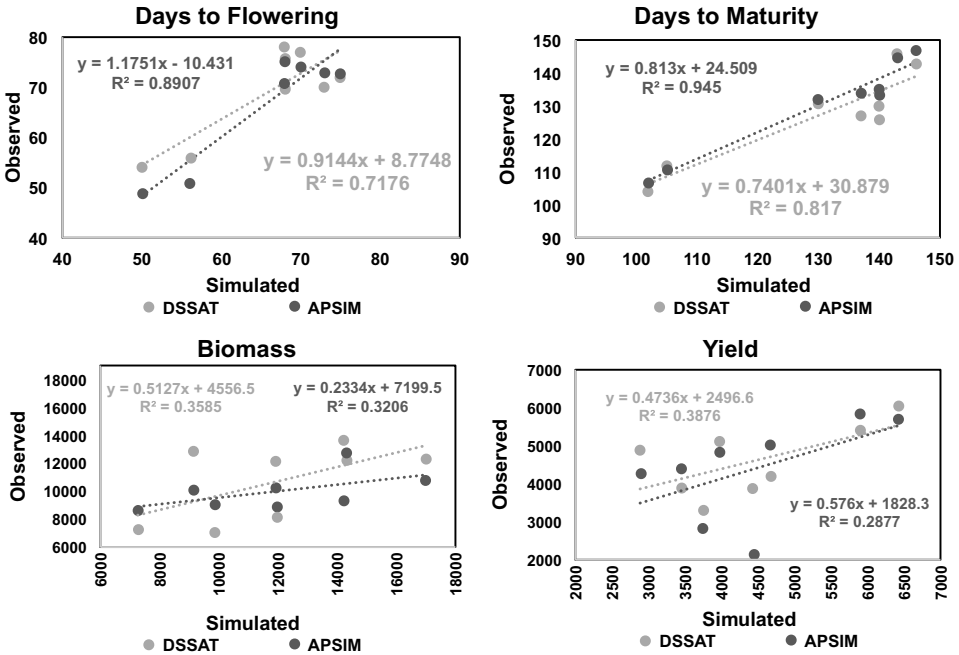


Fig. 9. Relationship between DSSAT and APSIM simulated and observed days to maturity, days to flowering, grain yield (kg/ha), and biomass yield (kg/ha) for the varieties H511 and H513.

the Katumani variety, default parameters already available with APSIM and DSSAT were used without any changes. In the case of H511 and H513, parameters were derived by manipulating the thermal time required to complete various growth stages until the simulated phenology matched the observed phenology. Simulations with the final set of parameters by both crop models indicated a good relationship between observed and simulated days to flowering and days to maturity (Fig. 9). However, the model-simulated biomass and grain yield did not display good agreement with the observed data. This is mainly due to lack of information regarding the management practices employed in these trials and lack of data on initial soil moisture and fertility conditions.

Additional model parameterization and validation

Model sensitivity to various environmental parameters was examined by conducting a matrix of simulations designed to understand the response of DSSAT and APSIM crop models to changes in maximum and minimum temperatures, precipitation, and atmospheric CO_2 concentrations. Embu climate data for 30 years (1980–2010)

Table 10. Response of maize to changes in temperature and rainfall in Embu County as simulated by APSIM and DSSAT.

	APSIM		DSSAT	
Treatment	Biomass yield (kg/ha)	Grain yield (kg/ha)	Biomass yield (kg/ha)	Grain yield (kg/ha)
Effect of temperature and rainfall				
Base Climate	9525	2207	4468	2450
Base+1°C	9181 (–4%)	2326 (+5%)	6711 (50%)	2461 (0%)
Base+3°C	8617 (–10%)	2593 (+17%)	7398 (66%)	2690 (10%)
Base+5°C	8001 (–16%)	2697 (+22%)	7788 (74%)	2811 (15%)
Base+1°C+10%RF	9364 (–2%)	2473 (+12%)	6383 (43%)	2343 (–4%)
Base+3°C+10%RF	8753 (–8%)	2681 (+21%)	7038 (57%)	2549 (4%)
Base+5°C+10%RF	8155 (–14%)	2814 (+27%)	7381 (65%)	2657 (8%)
Base+1°C–10%RF	9021 (–5%)	2187 (–1%)	6992 (56%)	2562 (5%)
Base+3°C–10%RF	8463 (–11%)	2424 (+10%)	7723 (73%)	2842 (16%)
Base+5°C–10%RF	7811 (–18%)	2628 (+19%)	8117 (82%)	2958 (21%)

RF=rainfall

were used for the sensitivity analysis. Table 10 compares the average maize yields simulated by the two crop models under different climatic conditions. In general, APSIM simulated higher biomass yield compared to DSSAT under all conditions. While both models simulated fairly similar responses in grain yield to changes in temperature and rainfall, they differed in the way total biomass was estimated. Simulations with APSIM indicated a decline in the total biomass, while those by DSSAT indicated an increase. A reduction in the crop growing period is considered as the main reason for reduced biomass production in the APSIM simulations, and the main contributor for higher biomass production with DSSAT is unclear since the CO_2 concentration in these simulations kept constant. APSIM is insensitive to changes in atmospheric CO_2.

Crop model results (*DSSAT and APSIM*)

After calibration, the crop models were used to simulate the yields of 440 farmers covered by the survey, by setting up farmer-specific climate, soil, crop, and management parameters. In order to evaluate the performance of the crop models in reproducing maize yields for the season 2011–2012 captured in the survey, simulations were made with DSSAT and APSIM for the short rainy season 2011–2012 for 160 farmers represented by the Embu climate. Since the required daily climate data for this season are not available for the other three meteorological stations (Ishiara, Karurumo, and Kindaruma), simulations were not made for the remaining 280 farms that are covered by these three stations. The simulated yields are generally higher

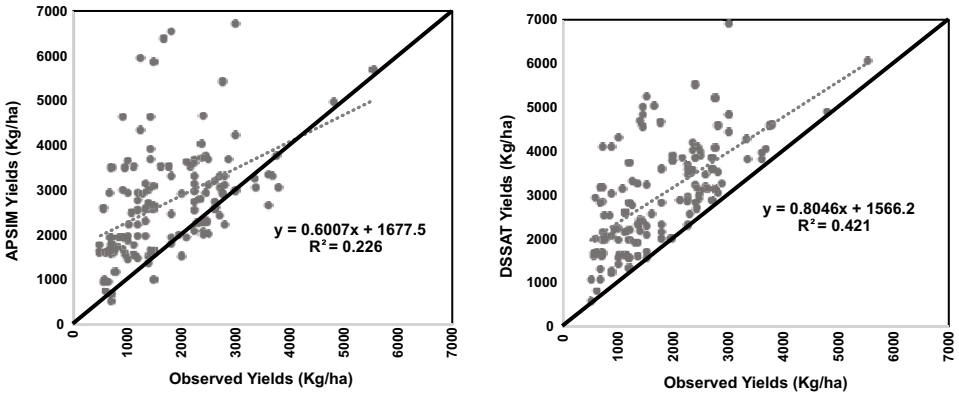


Fig. 10. Relationship between DSSAT and APSIM simulated grain yields and survey yields for the 2010–2011 short rain season in Embu County. (Black line in 1:1.)

than the yields reported by farmers (Fig. 10). The differences between simulated and observed yields varied from as little as 20 kg/ha to as high as 4000 kg/ha. This could be attributed to various factors such as differences in interpreting and translating farmers' descriptions of their resource endowment into model parameters, inability of the models to capture the effects of biotic stresses such as pests, diseases, and weeds, inaccuracies in estimating yields especially in the mixed/intercropping systems that are widely practiced, and inaccuracies in defining the initial conditions. However, the simulated long-term yields of the different AEZs reflected the trends in the yields reported by farmers fairly well, especially in the low-potential LM4 and LM5 AEZs. This is mainly due to high moisture stress experienced by the crops that, to a large extent, masked the effect of management and differences in the resource base.

Economics

Survey data and strata

Farm sizes in the region varied from one AEZ to the other but tend to be smaller in UM2 and larger in LM4 as shown in Table 11. The areas occupied by the different crops also varied from farm to farm and from season to season.

In general, yields of maize are very low mainly due to low levels of inputs used by the farmers. The average yields of maize varied from 1 t/ha in the relatively high-potential areas of UM2, UM3, and LM3 to 0.5 t/ha in the low-potential LM5. Maize yields did not vary significantly between SR and LR seasons in UM2, UM3, and LM3, but varied by about 200 kg/ha in LM4 and LM5 (Table 12). This could be explained by depressed rainfall in the LR seasons in the two AEZs, which received

Table 11. Average farm size of the sample households in different AEZs of Embu County.

AEZs	Mean farm size (ha)	Standard deviation
UM2	0.91	0.75
UM3	2.21	2.80
LM3	1.85	0.97
LM4	2.43	3.41
LM5	1.74	1.22

Table 12. Average maize yields of surveyed households during SR and LR seasons in different AEZs of Embu County.

	Maize yields SR (kg/ha)		Maize yields LR (kg/ha)	
AEZs	Mean	Std. dev.	Mean	Std. dev.
UM2	1029.6	636.7	1187.3	632.6
UM3	1194.8	845.6	1120.8	787.5
LM3	1020.9	719.9	901.4	665.1
LM4	959.9	658.6	739.7	556.4
LM5	525.4	381.9	363.7	309.2

Table 13. Non-agricultural income (Kenya shillings per year) by source of surveyed households in Embu county.

Income source	Number of households	Mean	Std. Dev.	Min.	Max.
Formal employment	45	223,585	200,906	7,000	800,000
Business	221	110,761	118,001	1,800	960,000
Rental income	18	83,889	108,859	1,500	480,000
Off-farm labor	99	27,031	33,675	1,000	240,000
Remittances	39	28,446	44,130	2,000	240,000
Shares	5	49,600	84,468	2,000	200,000
Others	2	26,500	28,991	6,000	47,000
Total	328	122,366	150,009	1,500	960,000

Note: 1 USD=KSh. 85 at the time of survey.

a relatively low amount of rainfall during this season compared to the other three AEZs.

In addition to agriculture, farmers depend on income from other sources, which vary from formal employment and businesses to remittances from family members (Table 13). The key source of non-agricultural income for most farmers is business, followed by off-farm labor.

RAP narrative and development

RAPs were developed against a background of demographic and socio-economic developments in the country such as: (1) devolution of government[1]; (2) increasing population; (3) government plans to invest in fertilizer manufacture; (4) current government subsidies on fertilizers; (5) improved economic performance expected to cause shifts from agriculture to service industries; (6) government plans for expansion of irrigation (from the current 120,000 ha to over 1,000,000 ha); and (7) expected increase in extension services and application of climate information by farmers.

A combination of these factors is expected to change the future outlook and impact of climate change. For example, it is assumed that with increased family-planning campaigns and increases in literacy levels, family sizes are expected to decrease by 30% in future. There is also the expectation that farmers will diversify into other non-farming activities to supplement their incomes, and hence non-farming income will increase by 50%. Given the current family sizes, farm subdivision is expected to continue. However, this will be countered by rural–urban migration, as rural populations move to cities to search for better opportunities. The trend will be accelerated by devolution of political and economic power to the county level. This increased urbanization, lack of interest in agriculture among the youth, and devolution is expected to have a net effect of increasing farm sizes by 30%.

Dairy herd sizes are expected to remain the same, although farmers in LM4 and LM5 might abandon their traditional breeds and opt for higher-yielding breeding so as to increase their milk output. With increased urbanization and growing population, the demand for milk is expected to increase and the price of milk to rise by 50%. However, it is expected that the cost of milk production will increase by 20% due to a shift towards processed feeds, which are more costly.

In crop production, there has been a sustained increase in the price of fertilizers in the past few years. This trend is expected to continue, but there are two factors that might slow it and even overturn it: The planned establishment of a fertilizer factory by the Kenyan government and the discovery of oil in Kenya. The net effect is an estimated 20% decline in fertilizer prices. There has also been an increase in improved maize seed prices due to increased demand by farmers. At the same time, the seed sector has witnessed increased competition due to entry of many competitors, which might slow seed price increases. The AgMIP RAP for the region therefore predicts an 80% increase in seed prices. The other component of variable costs expected to change is the cost of hired labor. This is because many people would opt to work off the farm, as the reward to labor from farming is not giving

[1] With the promulgation of the new constitution, Kenya has been divided into 47 county governments, and each has a different development agenda. Different policies in areas of agricultural development, food security, and poverty alleviation, etc., are expected to evolve from the different governments.

them enough compensation. Many young men are opting for other jobs such as transporting people and goods using motorbikes (*boda bodas*), and this is taking labor out of agriculture. The cost of labor is therefore expected to increase by 60%. The prices of other crops such as coffee, beans, and sorghum/ millet are expected to increase by 10%. This information is summarized in Table 14 below.

Adaptation Package

Strong trends in climate change showed the increasing scale of potential climate impacts on local crop varieties and crop management practices in the study area. Potential adaptation options vary with the scale of projected impacts. Since maize crop yields are marginally increasing or decreasing in the future projected climate change scenario, we show the implementation of better performing crop varieties with best crop management practices can cope with a harsh and highly variable climate. Developing adaptation measures based on the best performing crop variety, crop management practices, and suitable planting date is likely to have substantial benefits under a moderate climate change scenario.

Adaptation planning incorporates scientific information both from projections of climate and its impacts on crop productivity. There is a high diversity of agricultural practices in the study region because of the range of climate and other environmental variables and economic factors. Here we present a framework of adaption options based on the performance of crop varieties, crop management practices, and planting windows in the study areas. From the above crop simulation results it is evident that both the crop models APSIM and DSSAT show marginal changes in maize crop yields in the future projected climate change scenarios. Local crop varieties with current management practices showed decreased crop yields. Based on the

Table 14. Plausible changes in institutional and socio-economic indicators in the RAPs of Embu County.

Category	Variable/ indicator	Direction of change	Magnitude of change	Change over the period (%)
Institutional/policy/ regulation	Fertilizer prices	Reduced	Moderate	20
	Seed prices	Increase	High	80
	Milk prices	Increase	High	50
	Grain prices	Increase	Very High	200
Socio-economic	Labor cost	Increase	High	60
	Farm sizes	Increase	High	30
	Household sizes	Decrease	High	30
	Non-agricultural incomes	Increase	High	50

Table 15. Main components of the adaptation strategies developed for different AEZs in Embu County.

	Adaptation strategy for LR season				Adaptation strategy for SR season			
AEZ	Planting time	Plant pop.	Variety	Fertilizer	Planting time	Variety	Plant pop.	Fertilizer
LM3	15–30 Mar	50	H513	60	1–15 Oct	Deka_lb	50	80
LM4	15–30 Mar	50	Deka_lb	60	15–30 Oct	H511	50	70
LM5	15–30 Mar	50	H511	60	1–15 Nov	Deka_lb	40	60
UM2	15–30 Mar	50	H513	80	1–15 Nov	H511	40	70
UM3	15–30 Mar	50	H513	70	1–15 Oct	H513	40	60

above analysis, the better-performing crop varieties along with sustainable crop management practices were selected as shown in Table 15.

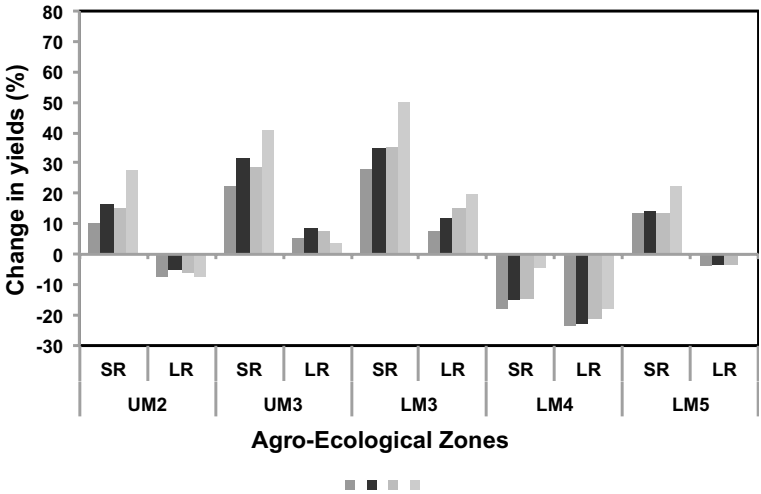
Core Question 1: What Is the Sensitivity of Current Agricultural Production Systems to Climate Change?

Impact of climate change on crop production

Simulations were carried out with both DSSAT and APSIM for baseline and climate change scenarios for all combinations of RCPs 4.5 and 8.5 and time-periods mid-century (2050s) and end- century (2080s) for all 20 AOGCMs. While both APSIM and DDSAT predicted that maize yields will increase under future climate scenarios, the magnitude of this increase is higher in the case of DSSAT compared to APSIM. Results from the APSIM simulations projected that maize yields would marginally increase in UM2, UM3, and LM3 AEZs and decline in LM4 and LM5. In all AEZs, the projected changes are within $\pm 10\%$ range compared to yields with baseline climate. In the case of DSSAT, except for the LR season in LM4, maize yields increased by more than 10%, mostly in 20–30% range, across all AEZs and in both seasons. The highest increase is predicted in LM3, followed by LM5 and UM3. Though the percentage increase is high in LM5, the yields are very low in this AEZ. Compared to the LR seasons, the increase is higher during the SR seasons. The changes in crop yields varied from –27 to +79% in the LR season and from –36 to +80% in the SR season. LM3, represented by the Karurumo weather station, showed the highest increase. In both seasons, simulated maize yields showed an increase through time, as displayed in Fig. 11.

The predicted increase in maize yields under climate change scenarios is attributed to general increase in rainfall and temperatures remaining within the optimal range for maize production even with an increase of 2.5 to 4.8°C. The higher

(a)



(b)

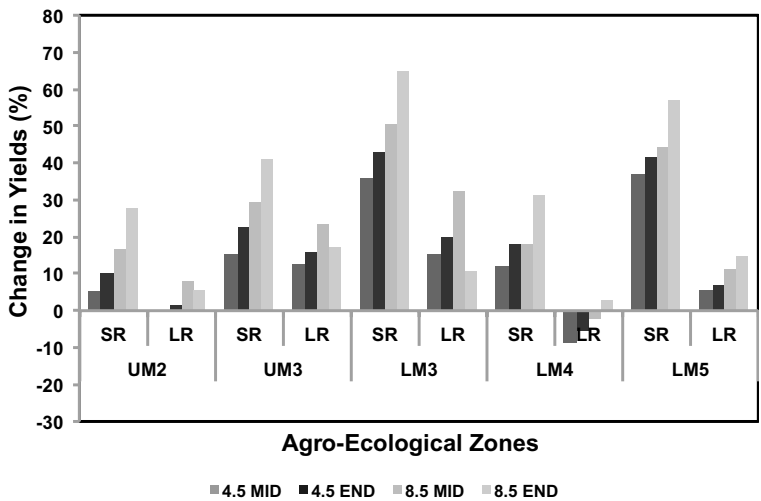


Fig. 11. APSIM (a) and DSSAT (b) simulated changes in average maize yields during SR and LR seasons under different AEZs in Embu County. (4.5 and 8.5 represent RCPs and Mid and End represent mid-century and end-century periods.)

increase observed during the SR season is due to a projected longer rainy season. The average number of rainy days in the LR season is 40 while in the SR it is 58 days as shown in Fig. 12. The fewer rainy days and shorter duration of the LR season exposed maize to water stress especially during the critical stages of flowering and grain-filling. Also most AOGCMs projected a considerably higher increase in rainfall during the SR season compared to the LR season. In the SR season, projected

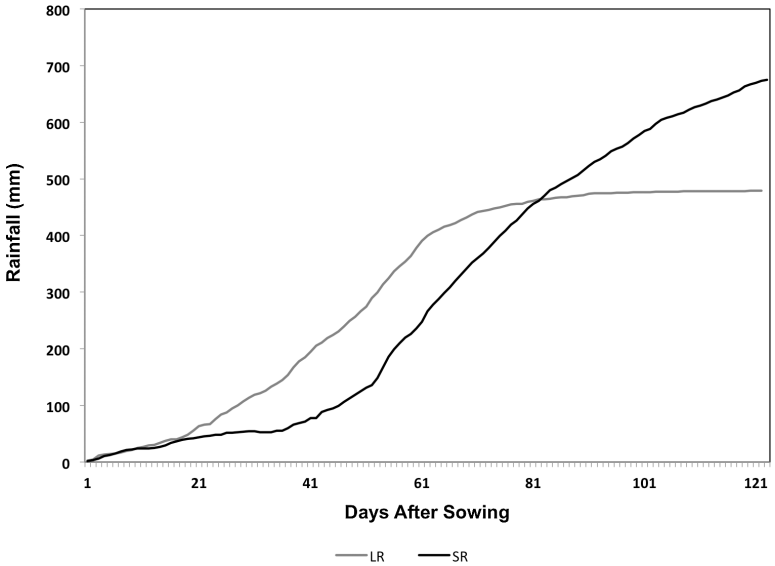


Fig. 12. Average cumulative rainfall during SR and LR seasons in Embu County.

changes in maize yields are as high as +60%, whereas those during LR season are up to a maximum of +30%, except for in LM4 where yields declined under future climate scenarios.

The differences in the yields simulated by APSIM and DSSAT are mainly due to the CO_2 effect. The version of APSIM used in this assessment is insensitive to changes in CO_2 concentration while DSSAT version has CO_2 effects included. To assess the effect of atmospheric CO_2 concentration on growth and yields of maize, simulations were carried out with DSSAT with and without changing CO_2 under projected climates from all the 20 AOGCMs. In the "without" scenario, the atmospheric concentration of CO_2 was set to 380 ppm and in the "with" scenario it was set to 450 ppm for RCP4.5 and 850 ppm for RCP8.5 scenarios. Maize yields showed a greater increase in the scenario in which CO_2 concentration was changed compared to the unchanged CO_2 scenario. The increase is fairly small in UM2 and UM3, as represented by the Embu climate, compared to the other AEZs. The CO_2 effect on maize yields was found to be much higher in the case of Ishiara and Kindaruma compared to Embu and Karuromo. In the case of LM4, represented by Ishiara, maize yields declined without CO_2 effect (Fig. 13) but increased when the CO_2 effect is included. The climate at Ishiara and Kindaruma sites is warmer by 2–3°C compared to that in Embu and Karuromo and use of inputs such as fertilizer is very low. In general, the increase in yields due to increase in CO_2 is in the range of 300–500 kg/ha. The very high percent increase in LM4 and LM5 is due to low level of base yields in these AEZs.

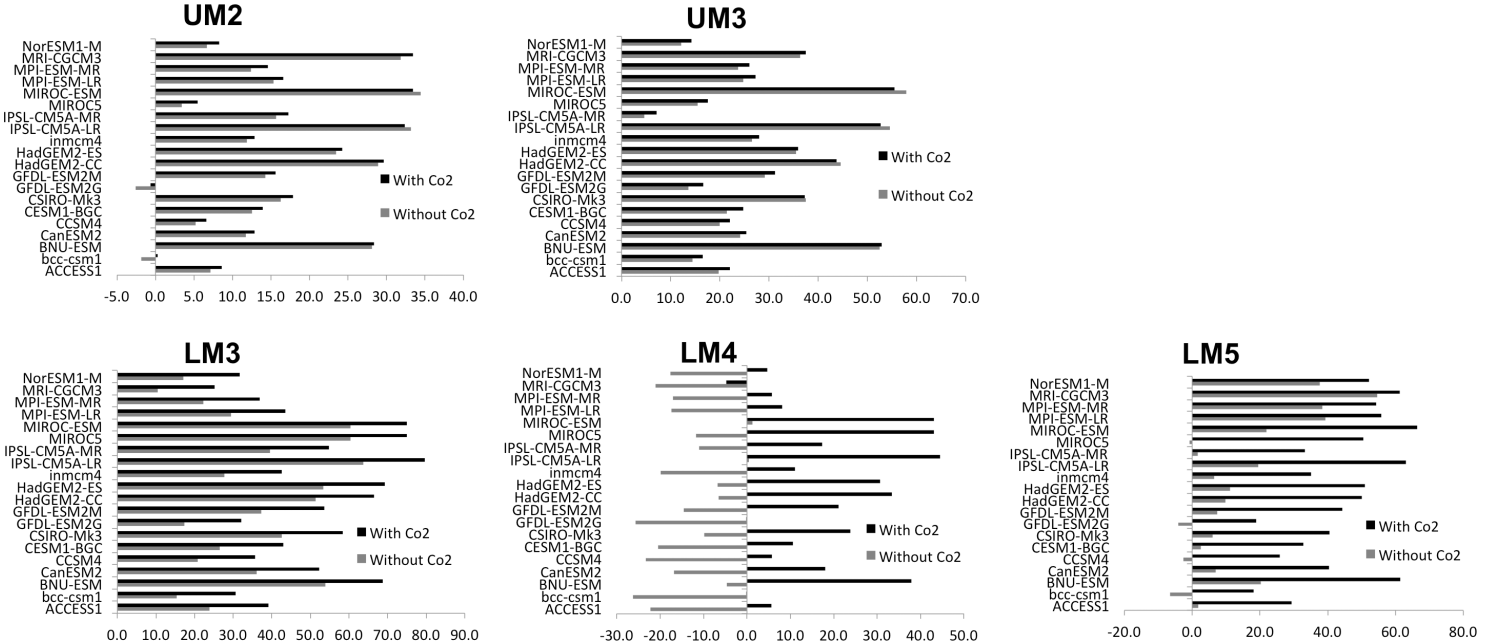


Fig. 13. Comparison of DSSAT projected changes in maize yields (percent deviation from baseline) with and without CO_2 fertilization effect under RCP 8.5 mid-century climate scenarios from 20 GCMs, at different agro-ecological zones of Embu County, Kenya.

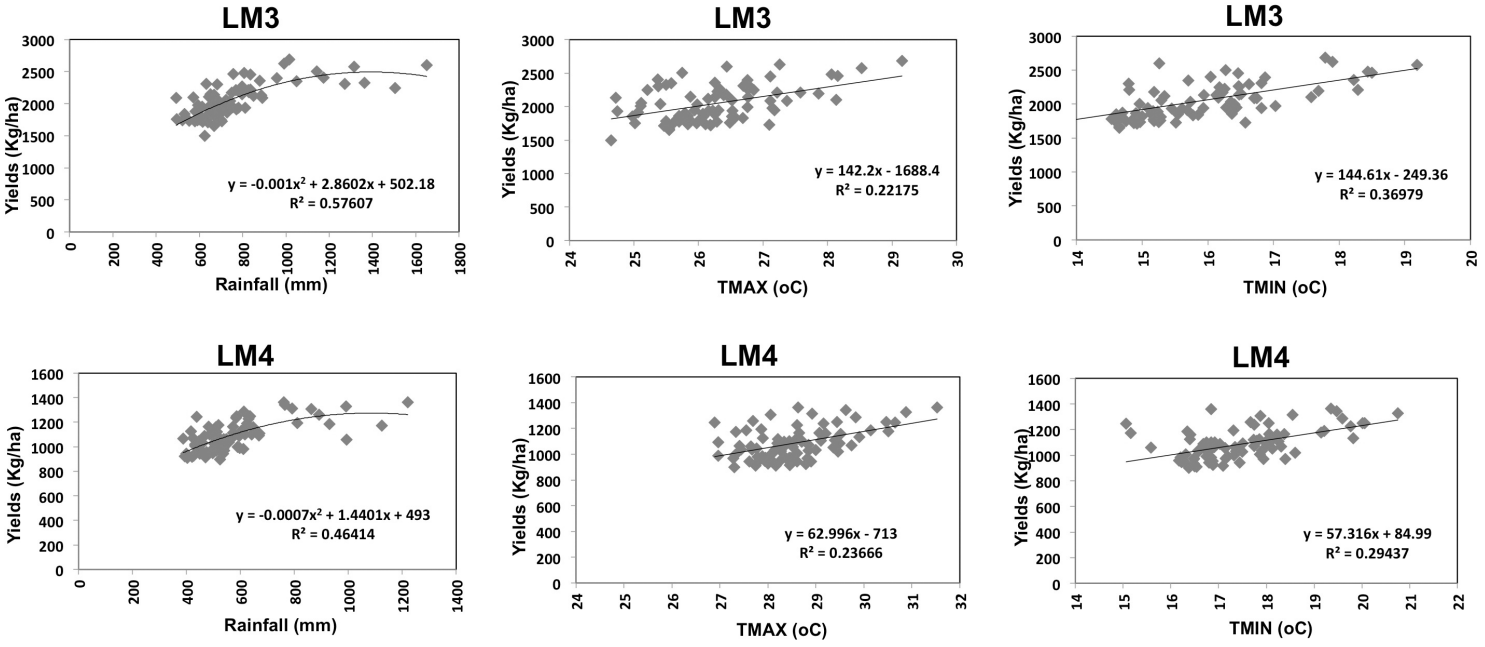


Fig. 14. Effect of rainfall and maximum and minimum temperatures on grain yields as simulated by DSSAT for two contrasting agro-ecological zones LM3 (above) and LM4 (below) in Embu county, Kenya.

Significant relationships between maize yield and rainfall, maximum and minimum temperatures, evapotranspiration, and crop duration were also observed in different AEZs. In all AEZs, maize yields are linearly related to the amount of rainfall during the crop season (Fig. 14). Analysis across the AEZs indicated that yields increased linearly with up to 700 mm rainfall. Further increase in seasonal rainfall apparently has no effect. Maize yields also showed a linear relationship with increase in seasonal maximum temperature between 25 and 30°C and with increase in minimum temperature between 14 and 19°C. Increased temperatures lead to faster growth and reduced duration of the growing season, which showed a negative impact on the performance of the crop.

The impacts of climate change on the performance of maize were also influenced by the management adopted by the farmers, such as crop variety used, planting time, plant population, and amount of fertilizer applied. These effects varied from one AEZ to the other. The local variety, Katumani, which is widely used by the farmers in the study area, is most vulnerable to projected changes in future climate (Fig. 15). Both APSIM and DSSAT simulation results show that Katumani is most vulnerable in the region, especially during the LR season. Katumani is a short-duration variety and further reduction of this growing period adversely affected its performance. In addition, it is a drought-tolerant variety and hence did not respond to the projected increase in rainfall. Farmers using low-input production systems were found to be less affected by changing climate compared to farmers with high-input systems. Adverse impacts of climate change were also observed in the case of farmers who planted late and used low plant populations. Use of higher plant populations seems

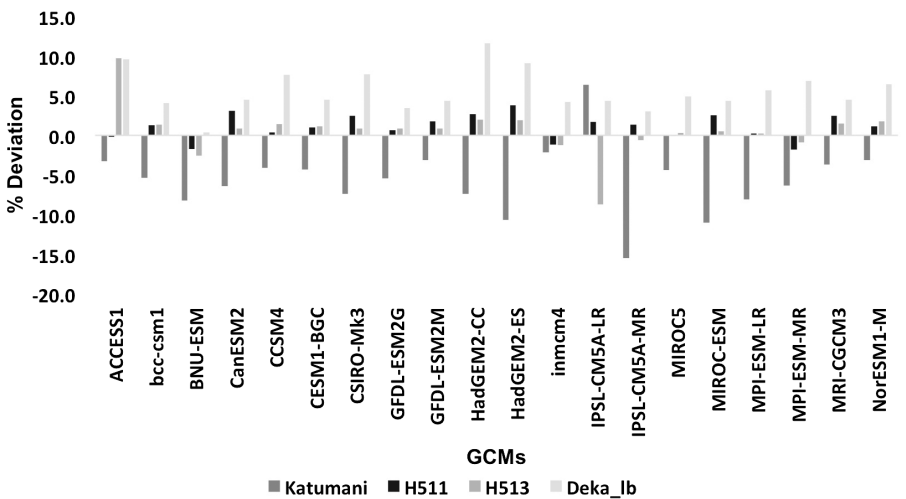


Fig. 15. Impact of projected changes in climate to mid-century under RCP8.5 on performance of different maize varieties in Embu County.

to be an important option in adapting to climate change in the study area since it is able to compensate for the impacts of reduced growth duration and to capitalize on the increased moisture availability.

AgMIP Core Question 1: What is the Sensitivity of Current Agricultural Production System to Climate change?

In order to examine the sensitivity of the current production system to climate change, potential impacts of climate change were evaluated on net farm returns, *per capita* income, and poverty by using economic model Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD). The main production system that characterizes the Embu region comprises maize and beans — mainly intercrop — in all AEZs, coffee in UM2 and UM3 and pigeon pea and sorghum in LM4 and LM5. To assess the sensitivity to climate change we considered two systems:

- System 1 = current climate-current technology.
- System 2 = future climate-current technology.

This implies that the current production system under current climate and current technology (system 1) is perturbed with climate change (system 2) to determine how it responds to climate shock. Impacts of climate change for maize were simulated using crop simulation models and perturbed weather data corresponding to different climate scenarios. The ratio of future and base simulated yields is the relative yield which is used as a correction factor for observed (survey) data on maize yields.

For non-modeled crops, i.e. beans, coffee, pigeon pea and sorghum, expert opinion and secondary sources were used to specify expected changes. For instance with climate change, bean production is expected to increase by 10% in UM2, UM3, LM3 and decline by 10% in LM4 and LM5. Coffee is grown in UM2 and UM3, both of which gain from climate change, hence its production is expected to go up by 20% in both AEZs. Pigeon pea and sorghum are drought-tolerant crops grown in marginal areas and are not expected to be adversely affected by climate change. In fact, the increment in rainfall and temperature simultaneously in the region is expected to boost pigeon pea and sorghum production by 20% and 15%, respectively, in LM3 and decrease production of both crops by 10% in LM4 and LM5. Dairy production is also expected to increase by 10%. Output prices — both for crops and dairy — were also held constant for this scenario, but production costs are expected to change as production changes. Other household characteristics such as farm size, herd size, non-agricultural income, etc. are assumed to remain constant. Any change between the two systems is therefore purely the effect of climate on the current system.

From Table 16, if the current agricultural system is exposed to a climate shock, APSIM results for CCSM4 and MPI_ESM indicate that maize farmers in LM4 and LM5 will loose from climate change, while small positive changes are expected in UM2, UM3, and LM3. DSSAT results for CCSM4 and MIROC-5 indicate losses in maize production in LM4, while all other models indicate gains in maize production in all AEZs. The impact of climate change on non-modeled crops is illustrated in Table 17.

Results from TOA-MD simulations show that, if the current production system in Embu County is perturbed by climate change most of the AEZs would have positive impacts, except in the AEZs LM4 and LM5 where the percent of losers range between 25.8% and 62.3%.

APSIM simulations show that about 36.4% to 56.2% of the farmers in LM5 and 33.8% to 62.3% in LM4 are expected to be worse off than they are today if the current system was to be subjected to climate change (Table 18). The figures are lower for the same AEZs using DSSAT estimations. The percent losers in AEZs UM2, UM3 to LM3 are lower in both APSIM and DSSAT for all GCMs.

Climate change is expected to increase net farm returns as can be seen by comparison between net farm returns with and without climate change for the different GCMs (Fig. 16). In APSIM analysis, in all AEZs (except CCSM4 for AEZ LM4 and MPI-ESM for AEZs LM4 and LM5), climate change will cause an increase in net farm returns. With projections by some GCMs, maize production recorded declines and the positive incomes could be explained by rising returns from other crops (coffee, beans, pigeon peas, and sorghum), which are expected to increase in yields in some AEZs due to climate change. Examples of this are in CCSM4 in UM2 and MIROC-5 in LM4 which record a decline in maize production but increased net farm returns. In instances where loss in maize production and loss in other crops was recorded, net farm returns also recorded a decline e.g. CCSM4 for AEZ LM4; and MPI-ESM for AEZs LM4 and LM5. The gains in net returns are highest in LM3 and UM3 and lowest in LM5 (Fig. 16a). Results from the DSSAT model indicate gains in net farm returns in all AEZs and the trends are similar to those of APSIM, though higher (Fig. 16b).

Figures 17a and 17b show the gains and losses from climate change as a percent of net farm returns for the different models. APSIM simulations (Fig. 17b) indicate that GFDL recorded the highest net impact but also recorded the largest losses. The high net impact is comparable with the net impacts under DSSAT. HadGEM recorded the highest net impact from DSSAT simulations as can be seen in Fig. 17b, but the net impacts in DSSAT are similar. In both models, the magnitudes of gains and losses varies for the different GCMs, and this highlights the uncertainty in the analysis.

Table 16. Mean and standard deviation of relative yield of maize under climatic conditions predicted by five GCCMs under RCP8.5 to mid-century period in different AEZs of Embu County.

		Scenario 1: Sensitivity of current agricultural production systems									
		APSIM Time-averaged relative yield ($r = s2/s1$)					DSSAT Time-averaged relative yield ($r = s2/s1$)				
AEZ	Observed mean maize yield (kg/ha)	CCSM4	GFDL	HadGEM_2ES	MIROC-5	MPI_ESM_MR	CCSM4	GFDL	HadGEM_2ES	MIROC-5	MPI_ESM_MR
Upper Midland (UM2)	2191.20	0.97 (0.18)	1.06 (0.08)	1.07 (0.16)	1.06 (0.11)	1.03 (0.14)	1.12 (0.08)	1.17 (0.09)	1.07 (0.08)	1.11 (0.30)	1.23 (0.08)
Upper Midland (UM3)	2273.20	1.00 (0.20)	1.02 (0.22)	0.98 (0.20)	1.02 (0.16)	0.99 (0.17)	1.35 (0.43)	1.39 (0.43)	1.27 (0.42)	1.28 (0.64)	1.44 (0.48)
Lower Midland (LM3)	1935.09	1.02 (0.28)	1.03 (1.11)	1.00 (0.26)	1.02 (0.23)	1.00 (0.26)	1.32 (0.45)	1.51 (0.56)	1.63 (0.63)	1.24 (0.44)	1.41 (0.50)
Lower Midland (LM4)	1675.40	0.75 (1.14)	1.05 (1.64)	1.06 (0.52)	0.91 (1.27)	0.88 (0.45)	0.98 (0.33)	1.12 (0.39)	1.30 (0.43)	0.92 (0.32)	1.06 (0.35)
Lower Midland (LM5)	877.04	0.98 (0.39)	1.06 (0.44)	1.07 (0.52)	1.02 (0.56)	0.89 (0.39)	1.13 (0.27)	1.27 (0.37)	1.27 (0.47)	1.29 (1.68)	1.23 (0.33)

**Figures in brackets are standard deviations*

<1 indicates that climate change has a negative impact on production

>1 indicates that climate change has a positive impact on production

$r = s2/s1$ is the relative yield; where $s2$ is the future simulated yield and $s1$ is the base simulated yield

Table 17. RAPs for relative yields of non-modelled crops in different AEZs.

Crop	Beans	Coffee	Pigeon pea	Sorghum
Upper Midland (UM2)	1.1	1.2	N/A	N/A
Upper Midland (UM3)	1.1	1.2	N/A	N/A
Lower Midland (LM3)	1.1	N/A	1.1	1.15
Lower Midland (LM4)	0.9	N/A	0.9	0.9
Lower Midland (LM5)	0.9	N/A	0.9	0.9

Table 18. Percentage of farmers expected to be worse off (losers) with climate change in different AEZs in Embu County.

	APSIM					DSSAT				
AEZ	CCSM4	GFDL	HadGEM_ 2ES	MIRO C-5	MPI-ESM	CCSM4	GFDL	HadGEM_ 2ES	MIRO C-5	MPI-ESM
Upper Midland (UM2)	32.25	28.28	27.23	27.46	28.64	25.39	23.83	27.65	28.42	21.67
Upper Midland (UM3)	32.97	35.10	33.84	31.36	33.37	20.58	19.50	22.58	28.26	19.74
Lower Midland (LM3)	28.59	40.50	32.40	28.90	31.37	19.17	16.55	15.51	22.69	17.58
Lower Midland (LM4)	62.30	44.30	33.77	45.04	52.52	43.92	34.35	25.79	48.45	37.96
Lower Midland (LM5)	37.59	36.39	38.62	38.17	56.20	33.19	29.58	33.34	33.92	31.69
Aggregate	44.04	38.96	36.10	38.90	51.21	34.49	29.29	28.80	36.99	31.59

AgMIP Core Question 2: What Is the Impact of Climate Change on Future Agricultural Production Systems?

This scenario "translocates" the current production system into the future where production technology, prices and other biophysical and socio-economic conditions are changed. To assess the impact of climate change on this future system we incorporated information from RAPs discussed above, including yield and price trends. The two systems to analyze are defined as:

- System 1 = current climate-future technology with RAPs and trends.
- System 2 = Future climate-future technology scenario with RAPs and trends.

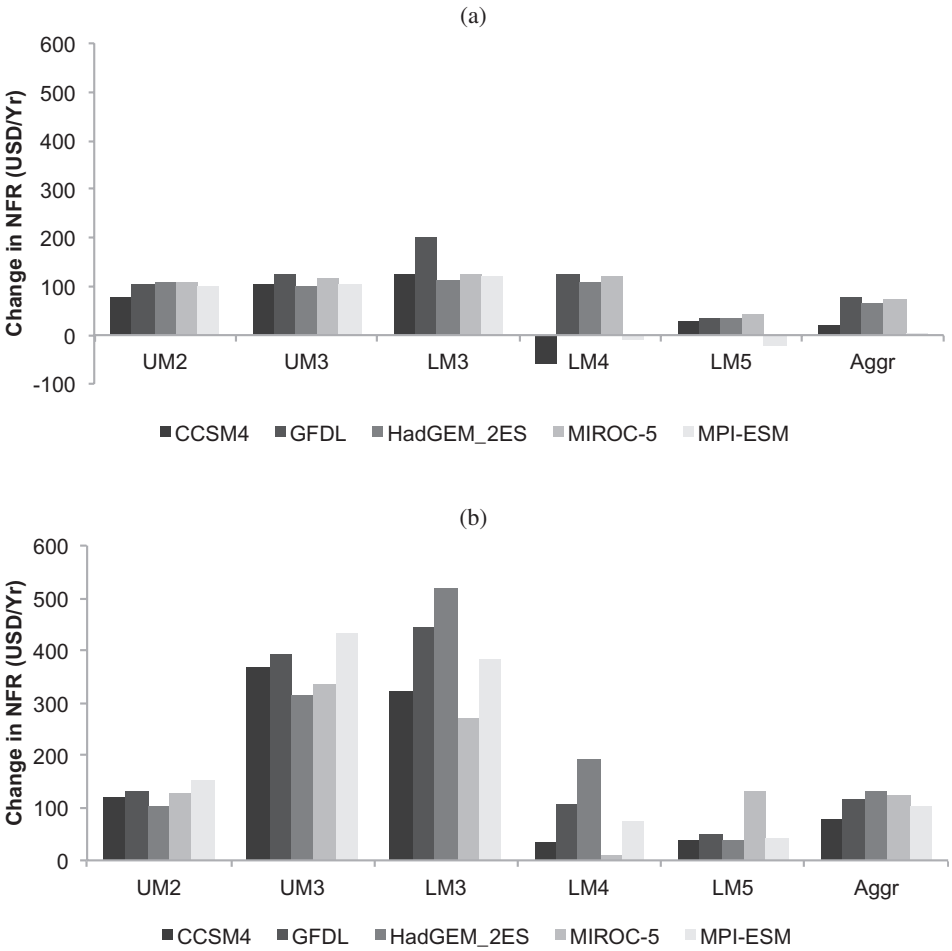


Fig. 16. Changes in net farm returns of farmers in different AEZs of Embu County, with and without climate change based on APSIM (a) and DSSAT (b) simulated yields.

Besides the RAP discussions from the country stakeholders, the global impact model also predicts future trends of production and prices for various crops. For instance, the model predicts that maize yields will increase by a factor of 1.4 while maize prices will increase by 1.35 in a situation without climate change and 1.95 for a situation with climate change. The yield trend factor for sorghum according to the global impact model is 2.00, while prices without and with climate change in the future are expected to increase by 1.19 and 1.48, respectively. Using historical information and expert opinion, we used yield trend factors of 1.5, 1.25 and 1.9 for beans, coffee and pigeon peas, respectively. For dairy production, we used a production factor of 1.4 for both systems. The costs of production in the future were assumed to follow the same trends as the commodity prices. The yield and price

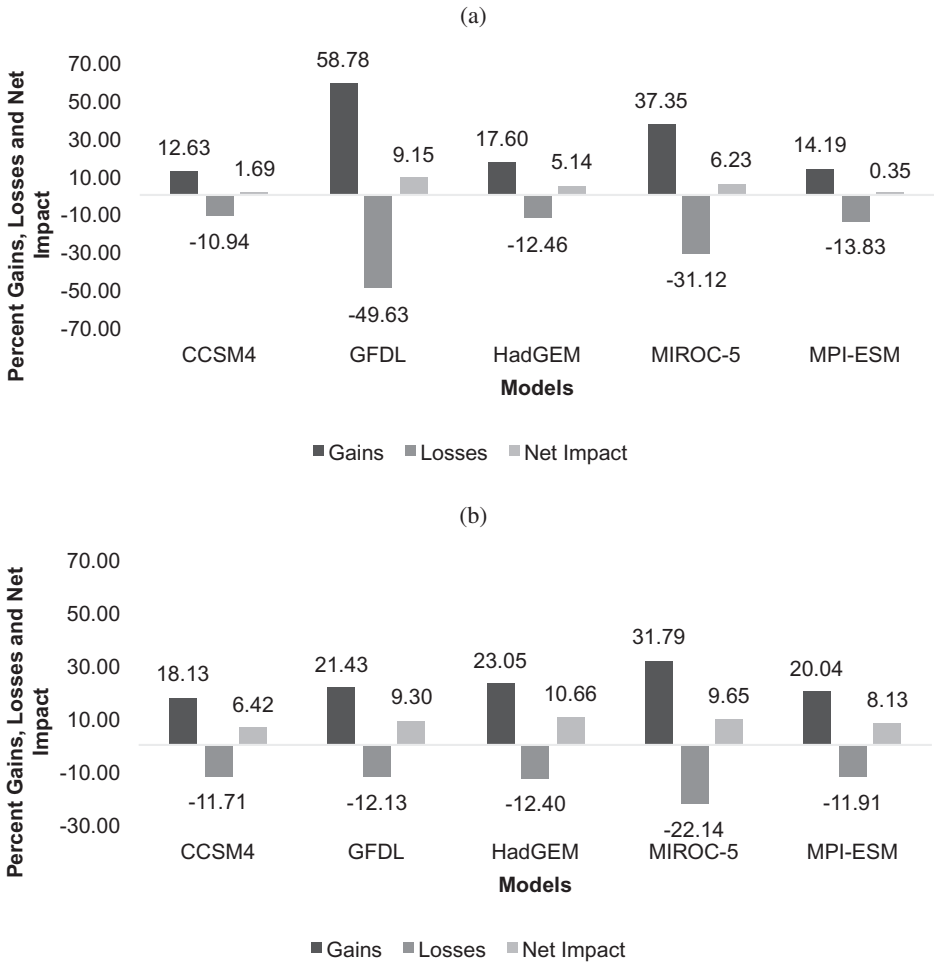


Fig. 17. Overall gains, losses and net impact as percent of net farm returns in Embu County, based on APSIM (a) and DSSAT (b) simulated yields.

inflation factors for both systems are shown in Table 19 below and were used to project the future systems with and without climate change

Results show that if the future agricultural production systems in Embu County are subjected to climate change, there will be losers from climate change in all AEZs. However, a comparison of the percent losers in this scenario is much lower than in Core Question 1. A comparison across the AEZs indicates that LM4 and UM3 will have the highest number of losers both for DSSAT and APSIM, while LM5 has the least number of losers. APSIM and DSSAT results seem to agree on the AEZs with the highest and lowest number of losers (Table 20). GFDL and MIROC-5 in

Table 19. Changes in yield and prices of different crops used in assessing the economic impacts of climate change.

Activity	Yield trends	Prices/costs System 1 Without climate change	Prices/costs System 2 With climate change
Maize	1.40	1.35	1.95
Beans	1.50	1.40	1.80
Coffee	1.25	1.60	2.00
Pigeon Pea	1.90	1.40	1.80
Sorghum	2.00	1.19	1.80
Dairy	1.40	1.50	2.00

Table 20. Losers from climate change under RAPs based future production systems in Embu County.

	APSIM				
AEZs	CCSM4	GFDL	HadGEM_2ES	MIROC-5	MPI-ESM
Upper Midland (UM2)	8.44	8.29	8.13	8.03	8.22
Upper Midland (UM3)	11.03	13.20	11.73	10.93	11.48
Lower Midland (LM3)	8.57	28.26	9.89	8.80	9.21
Lower Midland (LM4)	19.40	38.23	15.99	35.75	11.25
Lower Midland (LM5)	2.36	2.33	5.33	2.26	2.23
Aggregate	8.67	16.33	9.36	13.64	6.17
	DSSAT				
Upper Midland (UM2)	7.83	7.53	7.86	9.78	7.87
Upper Midland (UM3)	11.64	11.41	12.07	16.62	12.11
Lower Midland (LM3)	9.09	9.08	9.08	9.71	9.00
Lower Midland (LM4)	11.85	11.60	10.56	13.13	11.47
Lower Midland (LM5)	2.06	2.15	2.06	15.82	2.07
Aggregate	6.25	6.20	5.87	14.33	6.15

APSIM, and MIROC-5 in DSSAT are recording higher number of losers for some AEZs. The rationale behind the decline in the number of losers is the high trend values used for prices and yields to depict technological advancement and increased prices as we move in to the future. Technological changes and increases in food prices will ensure that farmers will have better yields and better incomes even in a future with climate change, but this is also countered by climate change impacts in some AEZs and increased cost of production. It should be noted that although costs are increasing, their magnitude is small compared to increase in revenue. This could be because of low agricultural input use in the area.

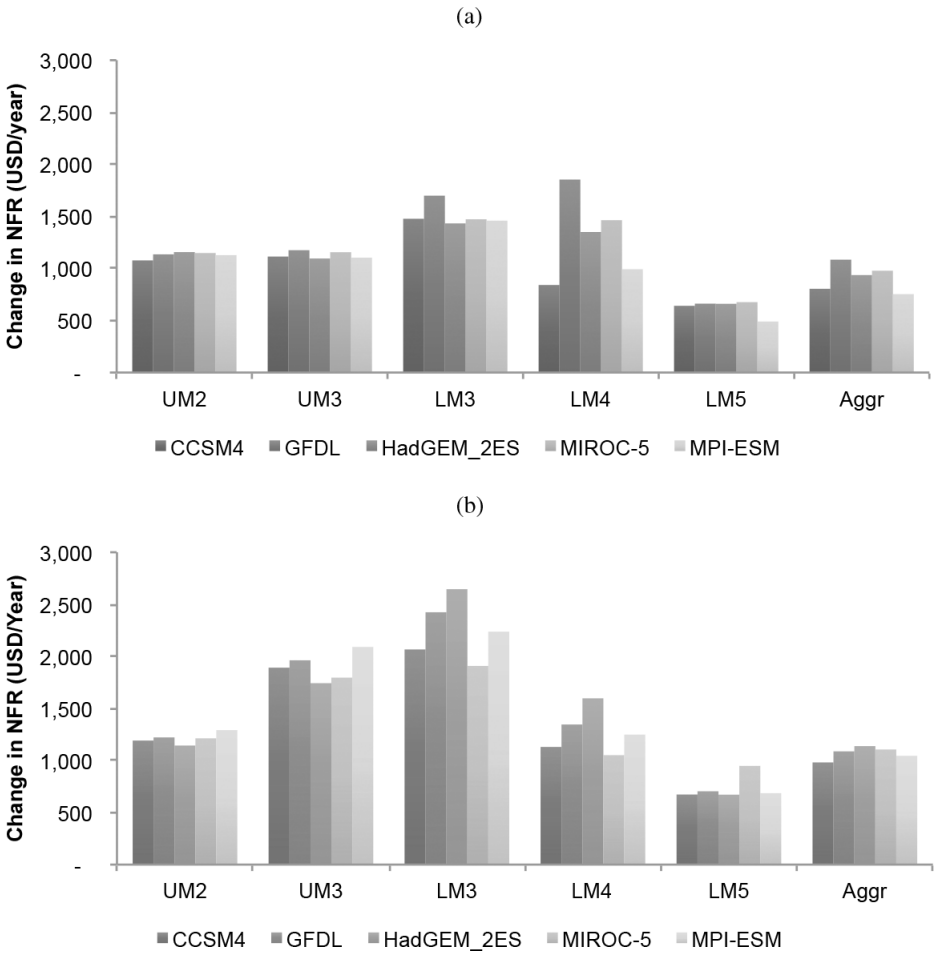


Fig. 18. Change in net farm returns in different AEZs of Embu County based on APSIM (a) and DSSAT (b) simulated yields and RAPs based future production systems.

The change in net farm returns are also significantly higher compared to those in Core question 1. The highest gains are in LM3 for APSIM, and UM3 and LM3 in DSSAT (Figs. 18a and b).

Figure 19 shows the gains and losses from climate change as percent of net farm returns for the different models. Both APSIM and DSSAT show higher increment in the net impact compared to simulations in Core Question 1. This is an indication that climate change in future will impact agriculture in the region more positively. However, this positive net impact could be attributed more to the trend values from the impact model than the impacts of climate change. These positive impacts in production and prices result in high farm net returns, increased *per capita* income and decrease in poverty rates. However, Figs. 19a and b show sizeable losses as well.

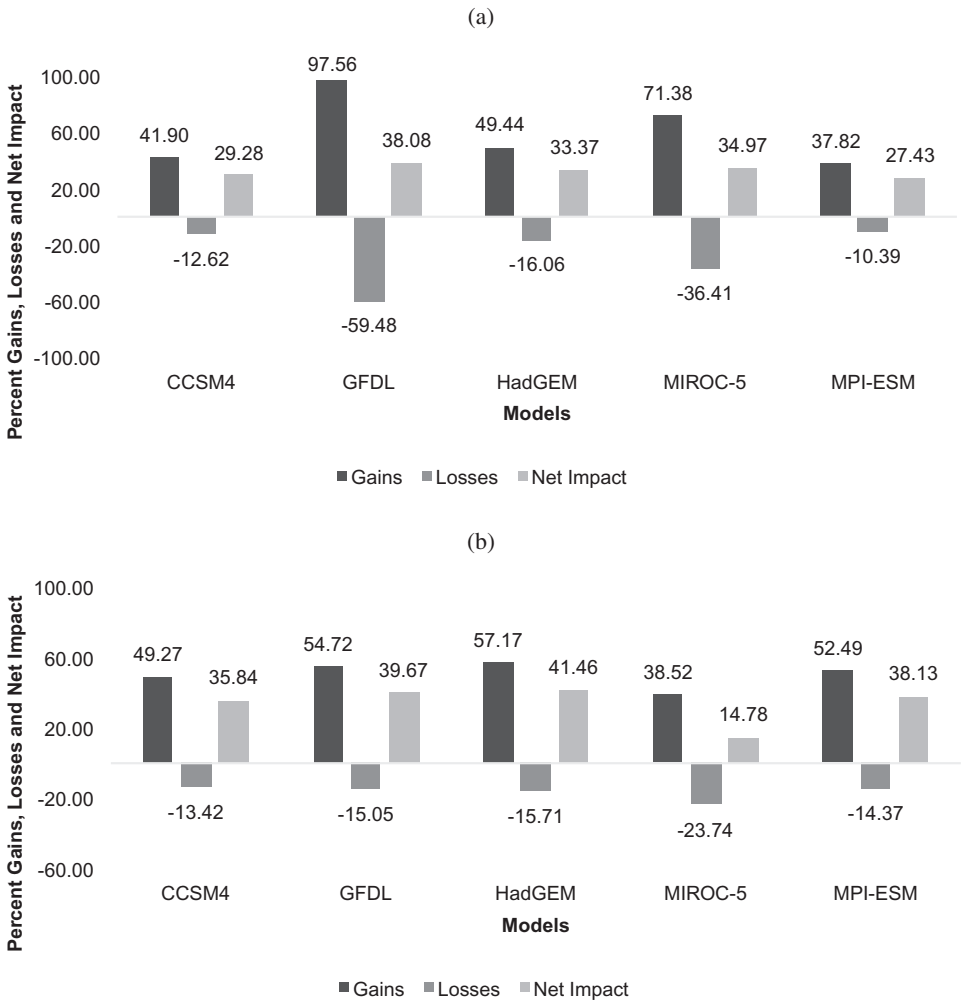


Fig. 19. Overall gains, losses and net impact as percent of net farm returns in Embu County, based on APSIM (a) and DSSAT (b) simulated yields and RAPs based future production systems.

The net impacts with APSIM simulations varied from 27.4% to 38.1% (Fig. 19a) while those under DSSAT (Fig. 19b) varied from 14.8% to 41.6%.

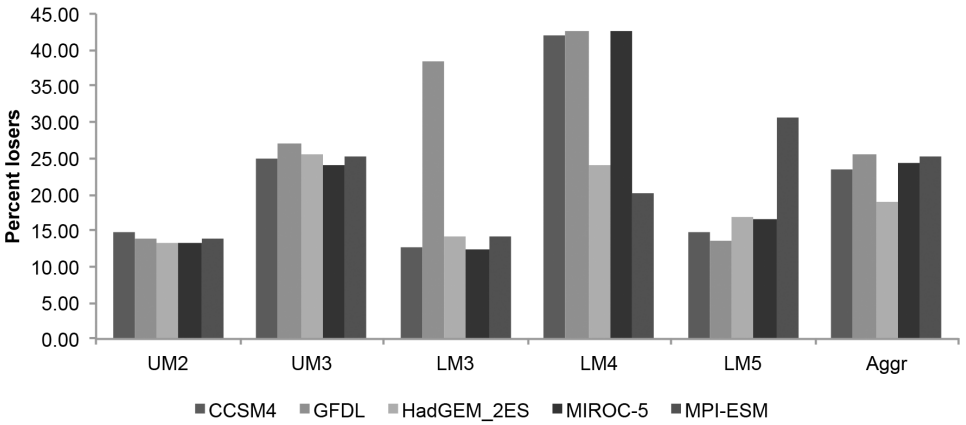
Sensitivity to Trends Assumptions

Projection of current systems to the future requires altering yield levels, commodity prices and production costs. To test how the results are sensitive to these assumptions, we lowered the trend factors for technology and prices, but increased the costs as shown in Table 21.

Table 21. Yield, commodity prices, and production costs used in the sensitivity analysis.

Activity	Production	Prices System 1	Prices System 2	Costs System 1	Costs System 2
Maize	1.15	1.3	1.6	1.6	2.0
Beans	1.2	1.4	1.6	1.5	2.1
Coffee	1.2	1.5	1.7	1.8	2.2
P Pea	1.2	1.4	1.6	1.6	1.9
Sorghum	1.1	1.2	1.4	1.8	2.1
Dairy	1.2	1.4	1.6	1.7	2.0

(a)



(b)

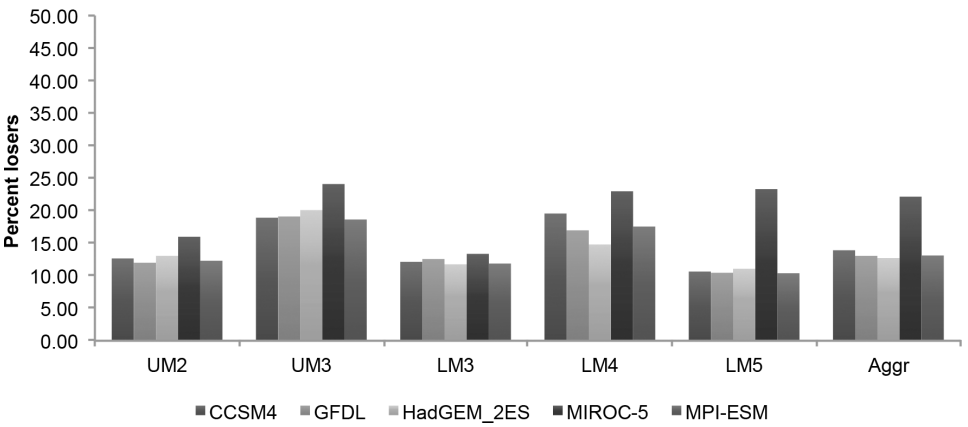


Fig. 20. Sensitivity of net impact of APSIM (a) and DSSAT (b) simulated yields under climate change to changes yield levels, prices and costs.

We then compared the net impact of these changes as a percent of mean net returns with those obtained with figures in Table 18. Results indicate significant differences in the number of losers for both APSIM and DSSAT (Figs. 20a and b), with the number being smaller in DSSAT.

In both models, the net impacts have reduced significantly, with net impacts reducing by almost half in all the GCMs (Fig. 21). This is an indication that model results are very sensitive to projected trends in yield, commodity prices, and production costs. Under or over estimation of these trends could lead to large differences in the economic impacts. Note that the relative yields of non-modeled crops have

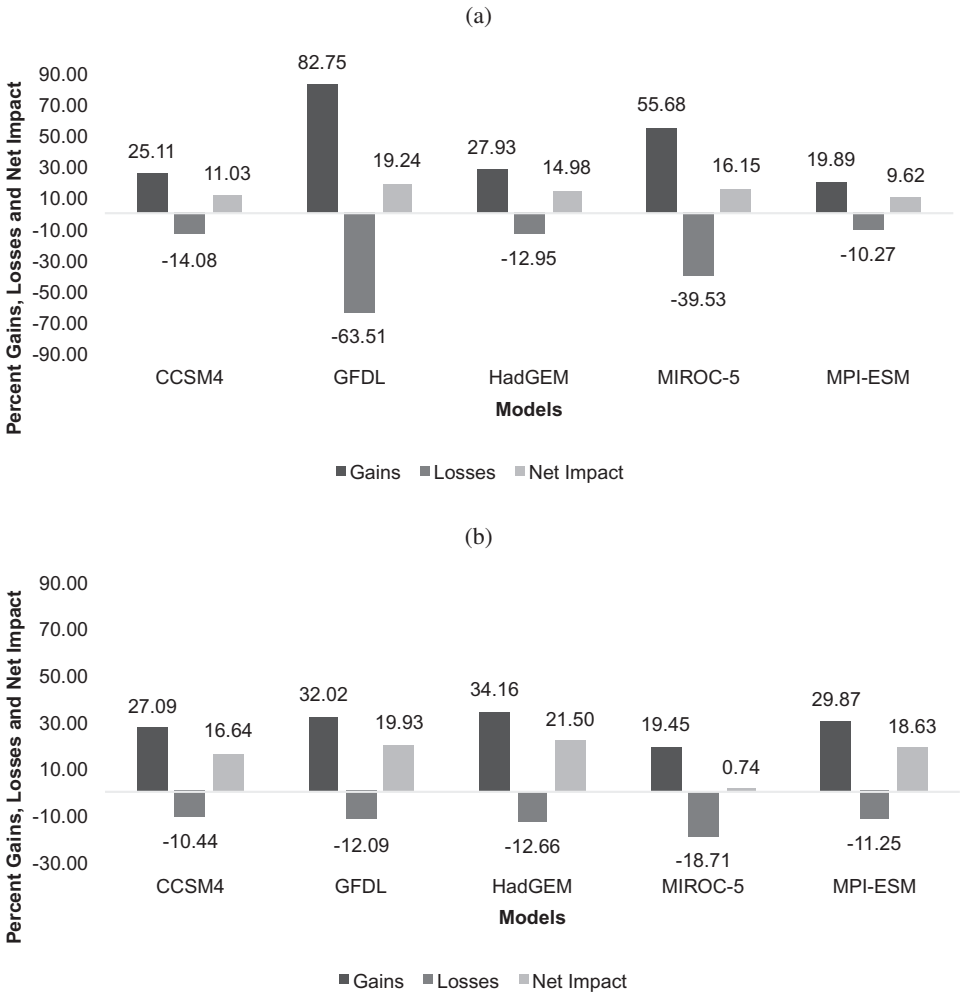


Fig. 21. Sensitivity of net impact of APSIM (a) and DSSAT (b) simulated yields under climate change to changes yield levels, prices, and costs.

not been changed. Changing them together with the trend factors can completely alter the results.

Core Question 3: What Are the Benefits of Climate Change Adaptations?

Impact of adaptation on crop productivity

Simulation analysis was carried out with both APSIM and DSSAT, with the new crop management strategies and selected varieties using baseline climates, and the downscaled CMIP5 AOGCMs future climate projections. DSSAT simulated maize-crop yields with adapted technology projected a significant increase across all the AEZs under RCP8.5 (Fig. 22) to mid- and end-century periods. With RCP8.5, maximum and minimum temperatures are projected to increase by 4.0 and 4.8°C, respectively and crop season precipitation amounts are projected to increase by +7% to end century.

Benefits of adaptation

In this scenario, the question we are answering is how the various indicators of net farm returns, income poverty and *per capita* income change if households in future system under climate change take up an adaptations package. Using TOA-MD, we assessed the impacts of the proposed adaptation package on *per capita* income, net farm returns and poverty. The assessment also determined the percentage of farmers in each AEZ who would adopt the proposed adaptation strategy. This scenario compares a future climate with future technology against a future climate-future technology with adaptations i.e.

- System 1 = Future climate-future technology with all RAPs discussed earlier and yield and price trend.
- System 2 = future climate-future technology with adaptation, RAPs and trends.

The adaptation package described above involves higher utilization of fertilizer and higher seeding rates, both of which imply increases in cost of production to the farmer. For this reason, the total variable cost of production is expected to increase. All the parameters corresponding to the other non-adapted production activities and household data were held constant.

From Table 22, we find that adaptation to climate change is expected to increase maize yields in all AEZs, with LM5 gaining the most from adaptations. A part of this increase is due to increased use of fertilizer and other inputs compared to current low levels of use by farmers in the region. With the increase in input use coupled with positive changes in climate, it is possible for farmers in the Embu County to double or triple their yields as shown in Table 22.

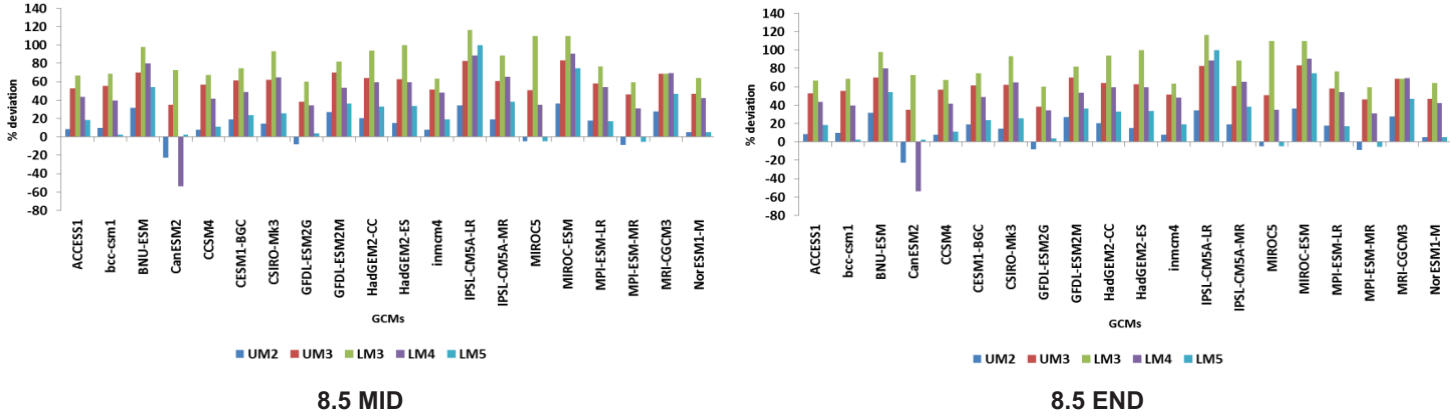


Fig. 22. DSSAT projected changes in maize crop yields for RCPs 8.5 and time-periods mid-century (2040–2070) and end-century (2070–2100) periods in Embu County.

Table 22. APSIM and DSSAT simulated mean maize yields (kg/ha) with adaptations in different AEZs of Embu County.

		Question 3: The benefits of climate change adaptations									
		APSIM Time-averaged relative yield ($r = s2/s1$)					DSSAT Time-averaged relative yield ($r = s2/s1$)				
AEZ	Projected future mean maize yield (Kg/ha)	CCSM4	GFDL	HadGEM_2ES	MIROC-5	MPI_ESM	CCSM4	GFDL	HadGEM_2ES	MIROC-5	MPI_ESM
UM2	5,151	1.61	1.50	1.68	1.61	1.56	1.17	1.24	1.25	1.05	1.00
UM3	5,377	1.52	1.48	1.52	1.53	1.50	1.70	1.45	1.77	1.64	1.59
LM3	5,136	1.10	1.07	1.10	1.09	1.09	1.47	1.28	1.66	1.44	1.36
LM4	4,060	1.60	2.04	1.84	1.46	1.57	1.66	1.96	1.99	2.09	1.58
LM5	1,941	2.96	3.14	3.15	2.85	2.92	2.01	1.89	2.40	1.70	1.70

<1 indicates that climate change has a negative impact on production

>1 indicates that climate change has a positive impact of production

$r = s2/s1$ is the relative yield; where s2 is the future simulated yield and s1 is the simulated base yield under current climate with current technology

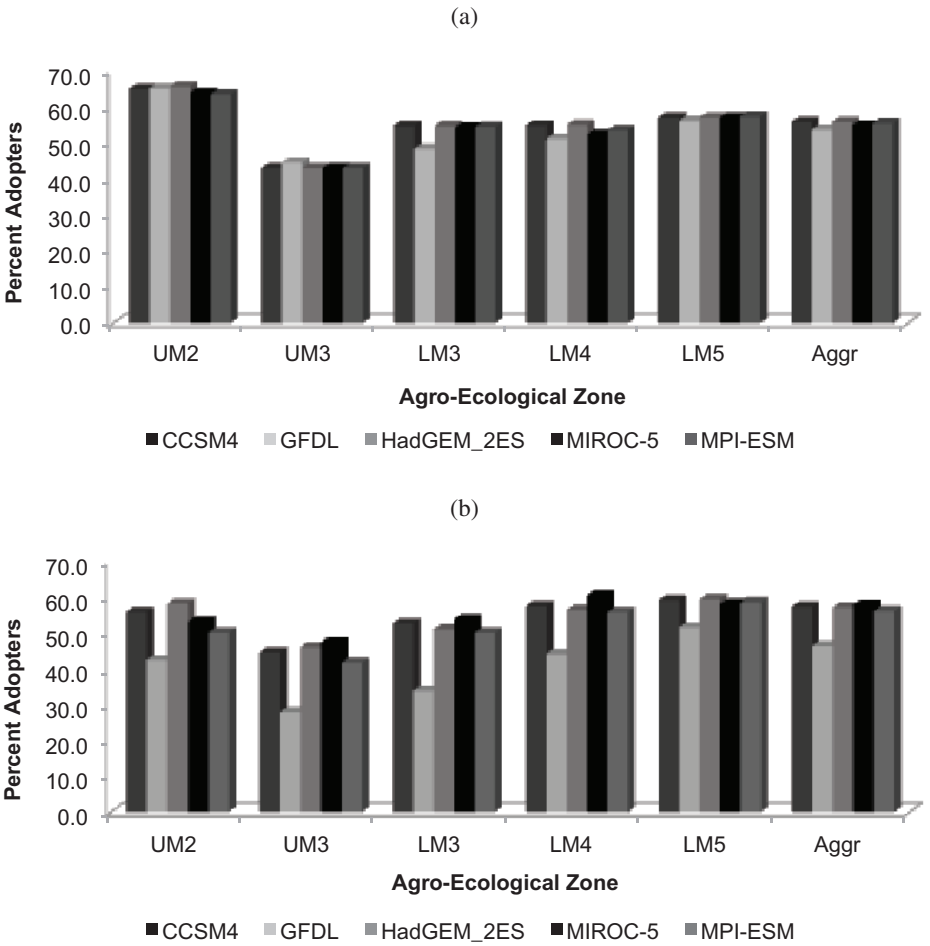


Fig. 23. Future adopters (%) of adaptation package in different AEZs of Embu County, based on APSIM (a) and DSSAT (b) simulated yields with adaptations.

We expect the high potential gains in yields to be matched by high percentages of adopters in all the GCMs. However, it is not expected that all farmers should adopt as autonomous adoption is a decision based on farmers' perceived gains from adopting the new technology. Simulations show that if the proposed adaptation strategy was to be introduced in future, APSIM predicts that farmers in UM3 would adopt the least while those in the other AEZs would take up the technology in larger numbers (Fig. 23a). The adoption rates are comparable in both models except for UM2 where APSIM is predicting significantly higher adoption rates than DSSAT (Fig. 23b).

The results show that there are substantial increases in net returns for farmers in LM4 and LM5 (both in DSSAT and APSIM) after adapting to climate change

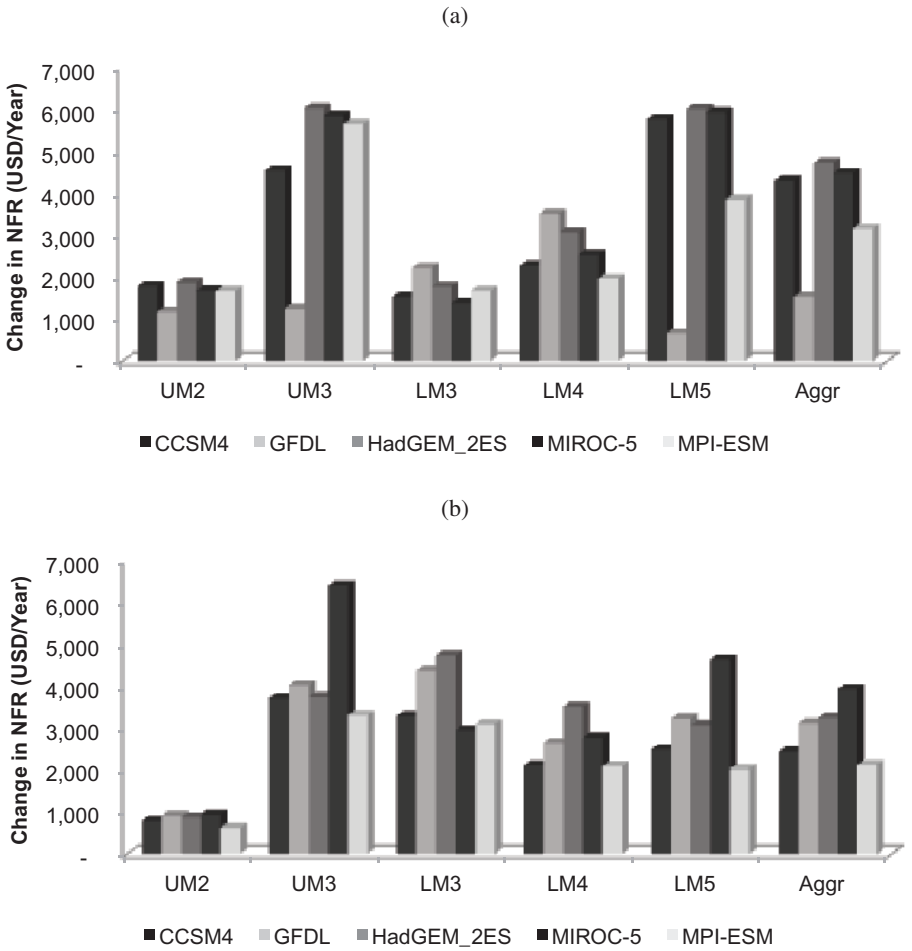


Fig. 24. Future net farm returns (USD/year) in different AEZs of Embu County based on APSIM (a) and DSSAT (b) simulated yields with adaptations.

(Figs. 24a and b). The farmers in these two AEZs have the highest yield gaps[2] and adaptation to climate change would substantially increase their returns. From Table 22, adaptation in these AEZs would increase yields by a factor of 1.58 to 3.15 depending on the model and the GCM.

Core Question 1 presented the gains/losses from climate change on future agricultural systems. However, if farmers decide to adapt to climate change, then there are extra benefits in net farm returns as indicated in Figs. 24a and b. Therefore

[2]This is the difference between actual and potential yield levels.

the adaptation benefits e.g. increased net returns, increased *per capita* income, and reduced poverty levels are over and above those under Core Question 1.

Conclusions and Next Steps

Realistic assessment of impacts of climate change on smallholder agricultural systems is a challenging exercise. Crop productivity in smallholder agricultural systems is a function of complex interactions of various suboptimal resources with large variations between fields, partly from inherent differences in soil types and partly due to differences in management. To estimate crop productivity under such circumstances, crop models must be sensitive enough to simulate the effects of biophysical heterogeneity and management strategies. Crop simulation models such as DSSAT and APSIM have the capabilities to capture these differences but require detailed data on climate, soil, and management. An additional challenge is to translate these impacts on productivity into socio-economic impacts on poor smallholder farmers who derive their livelihoods form these systems. This AgMIP regional assessment addressed this complexity in a comprehensive way by integrating the best available knowledge and modeling tools in the areas of climate, crop, and socio-economics. This probably is one of the first attempts in the region to assess the impacts of climate change on smallholder farming systems in a holistic and systematic way.

Despite data constraints and limitations, this assessment has demonstrated that it is possible to make a more reliable and credible assessment of impacts of climate variability and change on smallholder farming systems that can aid in planning for adaptation. The analysis provided good insights into the climate sensitivity of the various components of the smallholder farming systems in Embu County and identified the regions and components that are more vulnerable to projected changes in climate. It highlighted the differential impacts that the changes in climate can have on different AEZs within a small area that cannot be captured in the large-scale assessments made using aggregated empirical models.

The assessment further highlights the fact that in Eastern Africa, impacts of climate change will not be uniform, and that there will be losers and gainers depending on the environment they are operating in and the management employed. The assessment also reveals that to a large extent the negative effects of climate change can be minimized and benefits from the positive impacts can be maximized by making simple adjustments to the existing practices such as changing varieties, plant densities and soil fertility management. The planning and effectiveness of adaptation strategies can be greatly enhanced by this type of information, which helps in identifying the most appropriate interventions and also in targeting the most vulnerable

AEZs and people. In addition to technological advancement, predicted future prices can also offset negative climate impacts.

Contrary to conventional expectations where climate change is expected to have negative impact on agricultural production, this study has shown that climate change can have positive impacts in some locations. Embu, for instance is on the slopes of Mt. Kenya, and it is not representative of Kenya which comprises about 80% semi-arid lands. The temperatures in the area are also suboptimal for crop production. In fact for most GCMs in the region, improved temperatures would boost maize production. If this study is extended to other regions in the country e.g. the semi-arid regions, the results would be different. It is also feasible that the study over-estimated net farm returns due to low costs and high trend factors used to project prices and technology. The low costs could be due to low utilization of inputs among smallholder farmers, and also the feasibility that all production costs were not captured.

The methods and tools developed under this project proved to be extremely valuable in understanding and characterizing how smallholder agriculture in developing countries is going to be impacted by the projected changes in climate and by developing more appropriate site-specific adaptation strategies. Efforts are now required to further define the resource endowment and management employed by the farmers as accurately as possible to capture the diversity that exists among the farms. Once established, this will serve as a valuable platform to assess impacts of current schemes as well as future climate conditions. The framework will also serve as a means to develop climate-based agricultural forecasting and early-warning systems that can enable governments and humanitarian organizations to use appropriate responses to protect rural communities from the impacts of adverse extremes. The current assessment is limited to the impacts on maize only; this can be extended easily to cover most of the other enterprises that the farmers are involved with in the regions and to enable a more comprehensive assessment of the system.

Finally, there is a need to create awareness amongst the policymakers and decision-makers about the results and assessment capabilities, and to ensure that the relevant agencies and departments receive and utilize this information in planning various interventions, from adapting to impacts of climate change to providing food security assessments and early warnings.

References

Aaberge, R. and Mogstad, M. (2007). On the Definition and Measurement of Chronic Poverty, IZA Discussion Paper Series No. 2659, Institute for the Study of Labor, Bonn.

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., and Herrero, M. (2012). A method for evaluating climate change adaptation strategies for small-scale farmers using

survey, experimental and modeled data, *Agricultural Systems*, **111**, 85–95.

Cline, W. R. (2007). *Global Warming and Agriculture: Impact Estimates by Country*, Center for Global Development, Peterson Institute for International Economics, Washington, DC.

Fischer, G., Shah, M., Tubiello, F. N., and van Velhuizen, H. (2005). Socio-economic and climate change impacts on agriculture: An integrated assessment, 1990–2080, *Phil. Trans. Roy. Soc. B*, **360**, 2067–2073.

Griffiths, J. F. (1972). *Climates of Africa. World Survey of Climatology Series*, Vol. 10, Elsevier, Amsterdam, p. 604.

Hastenrath, S., Polzin, D., and Mutai, C. (2007). Diagnosing the 2005 drought in equatorial East Africa, *J. Clim.*, **20**, 4628.

IBSNAT (International Benchmark Sites Network for Agrotechnology Transfer) (1989). *Decision Support System for Agrotechnology Transfer, version 2.1*, IBSNAT project, Department of Agronomy and Soil Science, University of Hawaii, Honolulu, Hawaii.

IPCC (2007). *Climate Change 2007: The Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; Chapter 11. Regional Climate Projections*, Solomon, S., Quin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L. (eds.), Cambridge University Press, Cambridge, p. 996.

IPCC (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (eds.), Cambridge University Press, Cambridge, p. 1535.

Jackson, I. J. (1989). *Climate, Water and Agriculture in the Tropics*, Longman, London.

Jaetzold, R., Schmidt, H., Hornetz, B., and Shisanya, C. (2007). *Farm management handbook of Kenya, Vol II, Natural Conditions and Farm Management Information*, Ministry of Agriculture, East Kenya, p. 573.

Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., and Naylor, R. L. (2008). Prioritizing climate change adaptation needs for food security in 2030, *Science*, **319**, 607–610.

McCown, R. L., Hammer, G. L., Hargreaves, J. N. G., Holzworth, D. P., and Freebairn, D. M. (1996). APSIM: A novel software system for model development, model testing, and simulation in agricultural systems research, *Agric. Syst.*, **50**, 255–271.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**, 747–756.

Omano, S. W., Diao, X., Wood, W., Chamberlain, J., You, L., Benin, S., Wood-Sichara, U., and Tatwangire, A. (2006). *Strategic Priorities for Agricultural Development in Eastern and Central Africa. IFPRI Report 150*, International Food Policy Research Institute, Washington, DC. Available at: http://www.ifpri.org/sites/default/files/pubs/pubs/abstract/150/rr150toc.pdf. Accessed on 22 September 2014.

Osei, W. Y. and Aryeetey-Attoh, S. (1997). "Geography of Sub-Saharan Africa", in Aryeetey- Attoh, S., (ed.), *The Physical Environment*, Prentice Hall, Upper Saddle River, NJ, pp. 1–34.

Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M., and Fischer, G. (2004). Effects of climate change on global food production under SRES emissions and socioeconomic scenarios, *Global Environ. Change*, **14**, 53–67.

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M. G., Schubert, S. D., Takacs, L., Kim, G. K., Bloom, S., Chen, J., Collins, D., Conaty, A., and da Silva, A. (2011). MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, *J. Clim.*, **24**, 3624–3648.

Rosenzweig, C., Jones, J. W., Hatfield, J., Antle, J., Ruane, A., Boote, K., Thorburn, P., Valdivia, R., Porter, C., Janssen, S., and Mutter, C. (2013a). *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.0*, AgMIP, New York.

Rosenzweig, C., Jones, J. W., Hatfield, J. C., Ruane, A. C., Boote, K. J., Thorburne, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Bassoi, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013b). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014). AgMIP climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol*., 200. doi: 10.1016/j.agrformet.2014.09.016.

Shongwe, M. E., van Oldenborgh, G. J., van den Hurk, B. J. J. M., de Boer, B., Coelho, C. A. S., and van Aalst, M. K. (2009). Projected changes in mean and extreme precipitation in Africa under global warming. Part I: Southern Africa, *J. Clim.*, **22**, 3819–3837.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An Overview of CMIP5 and the Experiment Design, *Bull. Am. Meteorol. Soc.*, **93**, 485–498.

Wilby, R. L., Charles, S., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. O. (2004). *Guidelines for use of climate scenarios developed from statistical downscaling methods*, IPCC Supporting Material. Available at: www.ipcc-data.org/guidelines/dgm_no2_v1_09_2004.pdf. Accessed on 30 September 2014.

Webster, P. J., Moore, A. M., Loschnigg, J. P., and Leben, R. R. (1999). Coupled oceanic-atmospheric dynamics in the Indian Ocean during 1997–98, *Nature*, **401**, 356–360.

United Nations (1995). *The Copenhagen Declaration and Programme of Action, World Summit for Social Development*, 6–12 March 1995, New York, United Nations.

Zhang, X. and Feng, Y. (2004). *RClimDex User Manual*, Climate Research Division, Science and Technology Branch, Environment Canada, p. 23.

Chapter 4

Projected Impacts of Climate Change Scenarios on the Production of Maize in Southern Africa: An Integrated Assessment Case Study of the Bethlehem District, Central Free State, South Africa

Yacob G. Beletse[1] Wiltrud Durand[2], Charles Nhemachena[3], Olivier Crespo[4], Weldemichael A. Tesfuhuney[5], Matthew R. Jones[6], Mogos Y. Teweldemedhin[7], Sunshine M. Gamedze[5], Pontsho M. Bonolo[7], Syanda Jonas[3], Sue Walker[5,8], Patrick Gwimbi[9], Thembeka N. Mpuisang[10], Davide Cammarano[11,12], and Roberto O. Valdivia[13]

[1]*Agricultural Research Council-Roodeplaat, Pretoria, South Africa*

[2]*Agricultural Research Council-Small Grain Institute, Potchefstroom, South Africa*

[3]*Human Sciences Research Council, Pretoria, South Africa*

[4]*University of Cape Town, Rondebosch, South Africa*

[5]*University of the Free State, Bloemfontein, South Africa*

[6]*South African Sugarcane Research Institute, Mount Edgecombe, South Africa*

[7]*Polytechnic of Namibia, Windhoek, Namibia*

[8]*University of Nottingham Malaysia Campus, Semenyih, Malaysia*

[9]*National University of Lesotho, Maseru, Lesotho*

[10]*Botswana College of Agriculture, Gaborone, Botswana*

[11]*University of Florida, Gainesville, FL, USA*

[12]*James Hutton Institute, Dundee, Scotland*

[13]*Oregon State University, Corvallis, OR, USA*

This page intentionally left blank

Introduction

Southern Africa is a predominantly semi-arid region with high rainfall variability, characterized by frequent droughts and floods (Fig. 1). The climate is highly seasonal with hot, wet summers and cool, dry winters. In summer, the Inter-Tropical Convergence Zone (ITCZ) is situated south of the equator and facilitates rainfall over the region during the growing season. Rainfall is typically convective and may be linked to large-scale synoptic features like mesoscale convective systems, tropical temperate troughs, and a thermal low in the subtropics. During winter, the ITCZ moves north of the equator and a high-pressure system with subsiding air forms over the region, which results in clear skies and dry, cool winters.

Agriculture plays a vital role in the economy in the region and sustains about 70% of the population, providing food, income, and employment (Southern Africa Development Community, 2013). The region is highly diverse in terms of cropping and socio-economic systems. The agriculture of the region is described as a dual system; it contains both well-developed commercial farming systems, which have large farms, and smallholder/subsistence-based production systems, which have smaller farms (Fig. 2). The commercial farming systems are characterized by large economic investments, modern crop management techniques with high inputs (e.g., nitrogen and water), an extensive use of labor, and market-based production. The

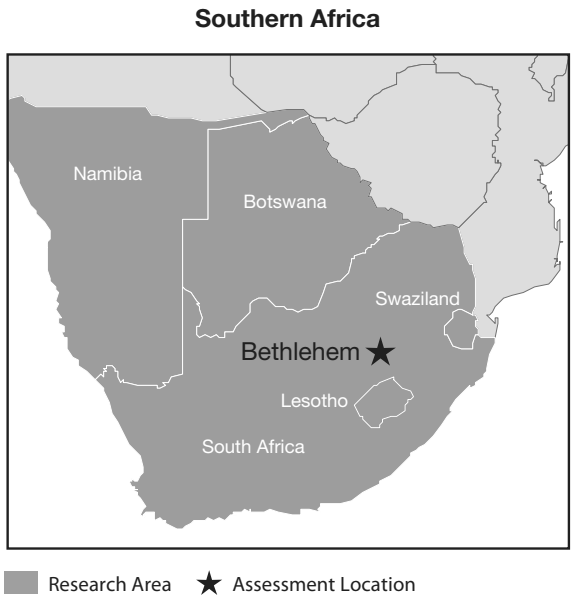


Fig. 1. Geographic location of countries covered in the AgMIP project: South Africa, Namibia, Botswana, Lesotho, and Swaziland.

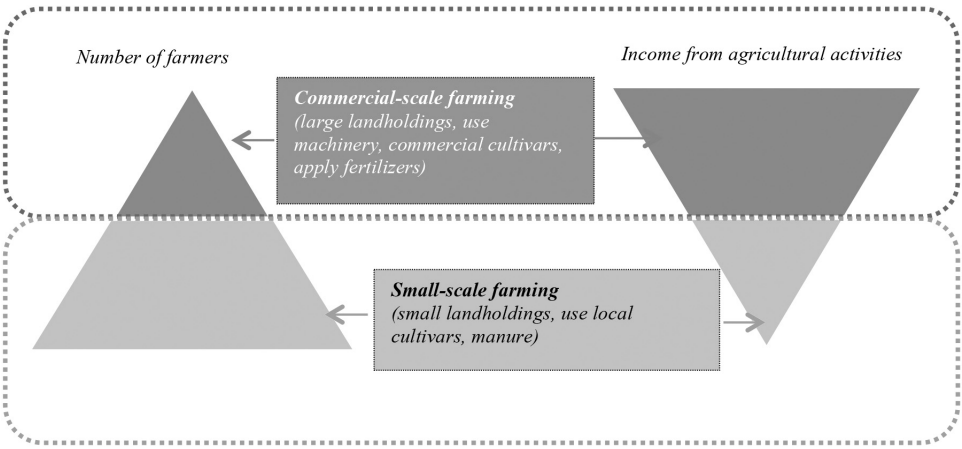


Fig. 2. Comparison of dual agricultural systems in Southern Africa, according to number of farmers, inputs, and income generated.

smallholder famers invest less money, and utilize fewer inputs and minimal labor. Their produce is directed to local informal markets.

The Southern African governments, through the Southern Africa Development Community (SADC), recognize the importance of agriculture to their economies and agree to cooperate on common agricultural policies and infrastructural developments (SADC, 2013). Most agricultural production under both systems in Southern Africa is rainfed, which means that the crops rely on rainfall to grow and produce yield. However, the impacts from projected climate change for this region pose very serious risks to future agricultural production, affecting commercial and smallholder farmers alike (IPCC, 2007). The possible impacts of climate change in the region are well documented (Davis, 2011; Engelbrecht *et al.*, 2009, 2013; Fischer *et al.*, 2005; Shulze, 2007; Tadross *et al.* 2005; Vogel, 1994).

Existing evidence for rainfall trends suggest a moderate decrease in annual rainfall, with high interannual rainfall variability since the late 1960s and more intense and widespread droughts (Fauchereau *et al.*, 2003; Kruger, 2006; Vogel, 1994). Other strong evidence, based on analysis of minimum and maximum temperature trends, indicates that the region is getting warmer (Hulme *et al.*, 2001; Schulze, 2007), which results in decreased water availability in rivers caused by increased temperatures and evaporation, coupled with shifts in the timing and amounts of rainfall (Davis, 2011). Water scarcity is also likely to have been exacerbated by changes in land use, poor land-use management, and political imperatives of improved access to household water for both rural and urban settlements (Kundhlande *et al.*, 2004; Meadows, 2006; Schulze *et al.*, 2001).

The important staple crops in Southern Africa are maize, wheat, sorghum, sugarcane, and potatoes. Maize is the most important crop grown, and accounts for up to 70% of total human caloric intake in the region (Byerlee and Eicher, 1997). Maize is produced throughout Southern Africa; the Free State, Mpumalanga, and North West provinces of South Africa are the largest producers, and account for approximately 83% of total production in South Africa (DAFF, 2013). During the 2011–2012 growing season the Free State province produced 40% of all commercial maize in South Africa, the North West produced 22%, followed by the Mpumalanga province, which produced 21% (DAFF, 2013). Maize is produced mostly in rainfed farming areas, which total about 1.9 million ha, compared to only 231,000 ha irrigated (NDA, 2007).

The three maize-producing provinces are situated on the central high plateau of South Africa. In these provinces, the annual rainfall varies from 400 mm in the west to more than 900 mm in the east. More than 75% of the rainfall occurs between November and March. However, a midsummer drought with accompanying high temperatures is a frequent occurrence, coinciding with the flowering period of maize, often causing poor pollination and consequently low yields. South African maize production is, therefore, generally characterized by high variations in yield due mainly to fluctuations in seasonal precipitation, with accompanying dry spells and high temperature.

Climate change projections show the potential for increased occurrence and severity of droughts for Southern Africa (Burke *et al.*, 2006; De Wit and Stankiewicz, 2006; Lobell *et al.*, 2008), a situation that is likely to increase the risk of crop failure. Although maize is adaptable to harsh conditions, warmer temperatures and less rainfall will probably have detrimental effects on production, thereby increasing food insecurity in the region (Akpalu *et al.*, 2009). The negative effects due to climate change that could occur on the production of maize and the ensuing changes in socio-economic conditions of farmers have not yet been established at the district level in South Africa

In the last three decades, global climate models (GCMs), crop models, and economic models have been used to assess the impacts of climate change on the production and prices of food crops (Singels *et al.*, 2010; Zinyengere *et al.*, 2013). Among various crop models, the Decision Support Systems for Agrotechnology Transfer (DSSAT) (Jones *et al.*, 2003) and the Agricultural Production System Simulator (APSIM) (Keating *et al.*, 2003) have been used in a broad range of applications, including assessments of climate change impacts on staple crop production systems. Weaknesses identified from previous climate change impact assessments are limited model intercomparison and multi-model assessments (Rosenzweig *et al.*, 2013) and that methods used to date are not well-suited to assess socio-economic impacts of climate change nor adaptation potential (Antle, 2011). Previous assessments failed

to represent the heterogeneity and technological detail essential to the analysis of adaptation (Antle, 2011). A number of modeling studies have examined the impacts of climate change on the link of crop yield to economic models, but few have explored levels related to risk of hunger (Challinor and Wheeler, 2008).

In order to capture such complex biophysical and socio-economic heterogeneities, and to improve understanding of agricultural impacts of climate change at national and regional scales in Southern Africa, a series of integrated climate change assessments using consistent methods and protocols of multi-model comparisons are required. The Agricultural Model Intercomparison and Improvement Project (AgMIP) has developed a range of crop, economic and climate modeling tools and methodologies for integrated climate change impact assessment that can be adapted in different regions depending on the data and resources available (Rosenzweig *et al.*, 2013). These methodologies have not been evaluated for district-level analysis of climate change impacts in the diverse agricultural systems of Southern Africa.

In this study, it is hypothesized that the AgMIP methodology could be used to provide better understanding of a range of possible future adaptation and socio-economic strategies that can be followed to lessen the impact of climate change in the region. The aim of the overall project is to evaluate the impacts of climate change on production of staple and nutritionally important crops in the region. These include maize, sorghum, sugarcane, wheat, and potatoes in the region (focusing on South Africa, Lesotho, Swaziland, Botswana, and Namibia). The objectives of this specific analysis are to compare historical and future maize production simulated by using DSSAT and APSIM, based on observed climate and future climate scenarios, and to characterize socio-economic outcomes in a selected district using the Trade-off Analysis Model for Multi-dimensional Impact Assessment (TOA-MD) (Antle, 2011; Antle *et al.*, 2014). The economic analysis of climate change impacts on crop production in Bethlehem focused on three main questions: (1) What is the sensitivity of current agricultural production systems to climate change? (2) What will be the impact of climate change on future agricultural production systems?, and (3) What can be the benefits of climate change adaptations? The results from the analysis are presented for each of these key questions. Considering the good data available for large-scale commercial farming systems in Southern Africa's Bethlehem district, in the Free State province, this location was selected for a specific case study.

Farming System Investigated

Description of the district

Bethlehem is located in the northeast of the Free state province, South Africa (28° 57' S, 25° 53' E, 1200 to 1640 m a.s.l. (above sea level)). The district was selected for

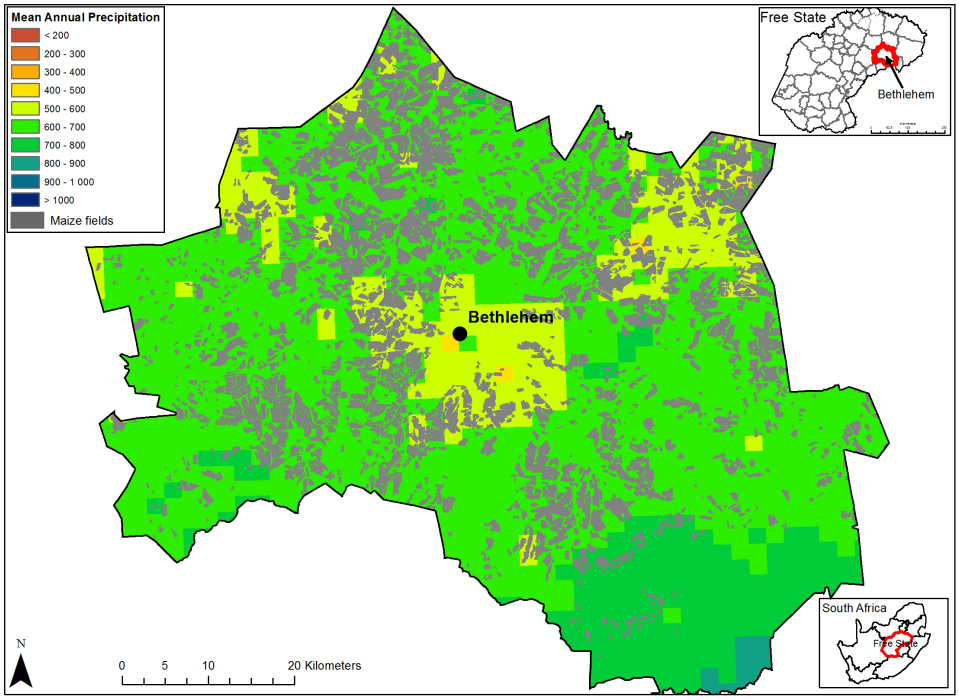


Fig. 3. Location of case study showing Bethlehem in Free State, South Africa. Colors represent amounts of rainfall (yellow (400–500 mm), light green (600–700 mm) and dark green (700–800 mm)). The gray color represents cultivated maize fields.

a case study because it is representative of large-scale commercial farming systems (Fig. 3). The climate of the region is characterized by summer rainfall (October–March), with an average rainfall of about 650 mm per year. January is the month with the highest average maximum temperature (30°C), whilst July is the month with the lowest average minimum temperature (1.5°C). Frost frequently occurs during the winter months due to the high altitude and proximity to the Drakensberg Mountains. Bethlehem has about 5000 fields planted to maize every year mainly under commercial farming systems.

Identification of fields for simulations

For the district-level integrated climate change impact assessment, detailed descriptions of the maize-farming practices were required. A household survey that provided information on each field was not available, so data were obtained from sources such as the field crop boundaries, objective yield surveys, land-type classification from different institutions, and interactions with local experts (Agricultural Research Council, personal communications; Table 1). In conjunction with the field crop

Table 1. Stakeholder interactions with local farmers and institutions across the identified SADC countries.

Stakeholders	Activities
Agricultural Research Council	Provided soil, climate and agronomic management data for the district.
Statistics South Africa	Economic data were made available.
Department of Agriculture, Forestry and Fisheries, Directorate: Plant Production Private Bag X250, Pretoria, 0001, Harvest House Building, Room 314, 30 Hamilton Street, Arcadia	Contact details of several potential data providers and stakeholders were provided.
Department of Agriculture Forestry and Fishery (DAFF), Climate Change and Disaster Management unit, and Plant Production Unit, South Africa	AgMIP approach and preliminary results on climate change impact assessment were presented to the DAFF. The DAFF facilitated access to data and future adaptation potential for the country. Attended workshop on Climate Change Sector Plan and Sectoral Disaster Risk Management Plan prepared by the DAFF.
University of the Free State	Assisted with arranging meetings with commercial system farmers and Agricultural Union members under Free State Agriculture and with arrangements to consult both large-scale commercial and small-scale farmers to obtain farmers' information and farm sizes.
Maize Working Group, South Africa	Agronomic information of maize in commercial farming for Mangaung district.
SENWES Coops (cooperatives) and Fertilizer Distributors, South Africa	Information about cultivar choices and application of inorganic fertilizers.
Cadastral office of Mangaung Municipality, Free State, South Africa	Assisted with information on farm size and location.

boundary database, satellite imagery was used to identify a total of 400 (out of the 5000) rainfed fields that had been planted to maize in Bethlehem. By using coordinated aerial photography and geo-positioning satellites (GPS) detailed field maps were derived with accurate (+/–3%) calculations of areas for each field. This was superimposed with the district soil survey data from ARC–ISCW (ARC, 2006), field information (such as field name, variety, plant spacing, plant densities, planting dates, fertilizer), and a climatological map.

Climate

Rainfall is projected to decrease over most of Southern Africa, particularly over the western and central regions, except over eastern South Africa and Mozambique

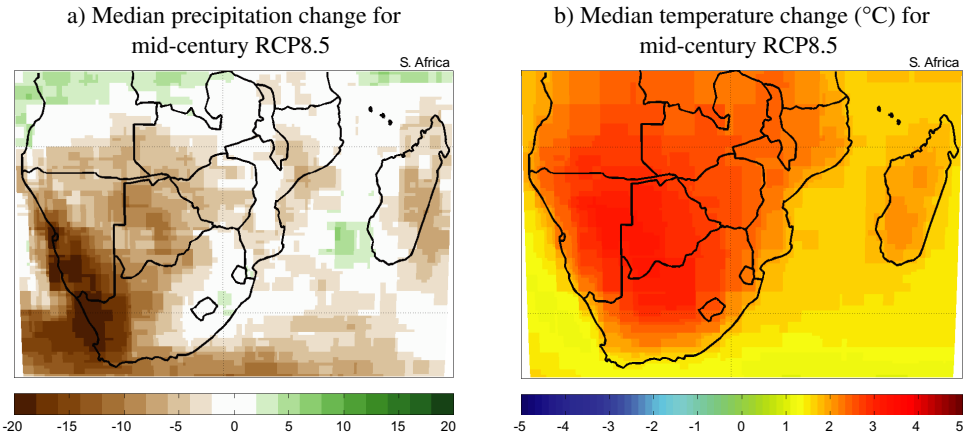


Fig. 4. Median precipitation (%) (a) and temperature (°C) (b) changes for mid-century (2040–2070) under representative concentration pathway (RCP) 8.5 for Southern Africa.

where the change is uncertain (Fig. 4). Temperature is projected to increase across the whole region. Changes range from large increases inland (above 3°C in southwestern Botswana and surrounding areas) to smaller increases in coastal areas. For the study site, the projections indicate no change in rainfall and temperature increases of at least 2°C for the period 2040–2070.

Figure 5 shows daily average temperature and precipitation change from baseline (1980–2010) to the mid-century 2050s (2040–2070) under the RCP8.5 scenario across all of the 20 GCMs.

Annual mean temperatures (Fig. 5a) are projected to increase consistently across the year and over all the GCMs. The range of projected temperature changes in winter (June, July, and August) is noticeably smaller in comparison with the other seasons, which would suggest an even greater confidence in projection for that season. Figure 4b shows the precipitation projections for Bethlehem, with the GCMs showing uncertainty in both the amount and the direction of change particularly during the summer months (December, January, and February). Future precipitation scenarios do not differ significantly from the baseline period, whether on a monthly, seasonal, or annual basis. The seasonal plot (Fig. 5) indicates that projected precipitation amounts are lower in July, August, and September compared to the current climate. Since rainfall changes are averaged per day, such a change could be the result of either lower amounts and/or less frequent rainfalls during those months. The uncertainty shown by the GCM rainfall rate (mm per day) projections emphasizes the need to consider the role of variability in the amount of rainfall received during each growing season for rainfed farming systems in semi-arid regions of Southern Africa. In Fig. 6, the 20 GCMs show a very strong agreement for increased temperature

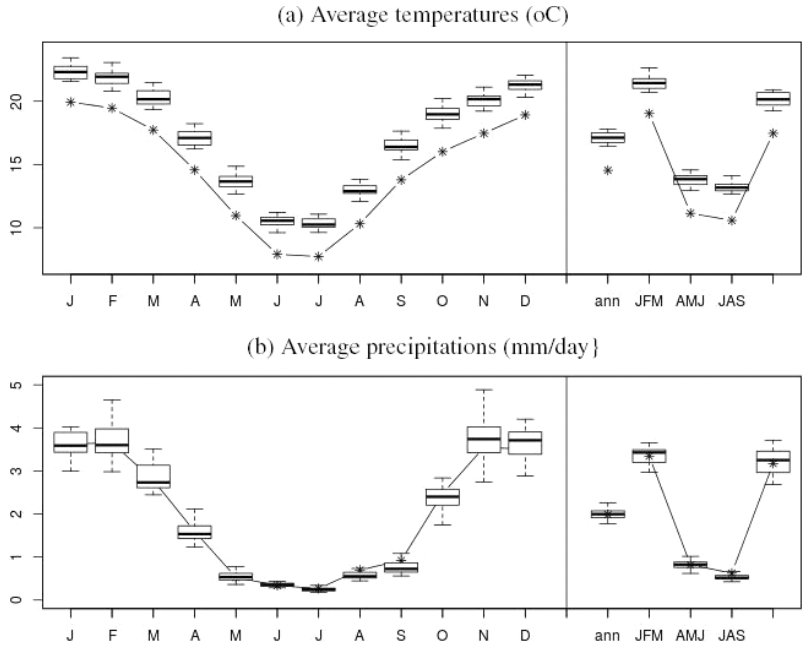


Fig. 5. Current (line and stars) and future (box and whiskers) monthly and seasonal mean (a) temperature and (b) precipitation, projected by 20 CMIP5 GCMs for Bethlehem in the 2050s under RCP8.5.

projections (+1.5 to +3.5°C), whereas projected changes in precipitation are variable, with some GCMs projecting increases and others decreases. Five GCMs were used in the full integrated assessment presented in this chapter, they are referred to as E, I, K, O, and R (see Table 5 for common identification). Those five GCMs give a fair representation of the temperature-change range. However, they do not represent the full range of rainfall scenarios of the 20 GCMs, since they project increases or no change only, while a number of the 20 GCMs project rainfall decreases.

If one considers the effect of the combined temperature and precipitation projections on the water balance of the region, one can expect that evapotranspiration would increase due to higher temperatures, and that precipitation could either increase to satisfy the water demand or decrease and result in a larger water deficit and a more arid climate.

Soil data

Soil characteristics needed by the crop models were described for each field individually using the land-type database (ARC, 2006) and pedo-transfer functions (van Tol *et al.*, 2012). Land type in this case is defined as an area with uniform

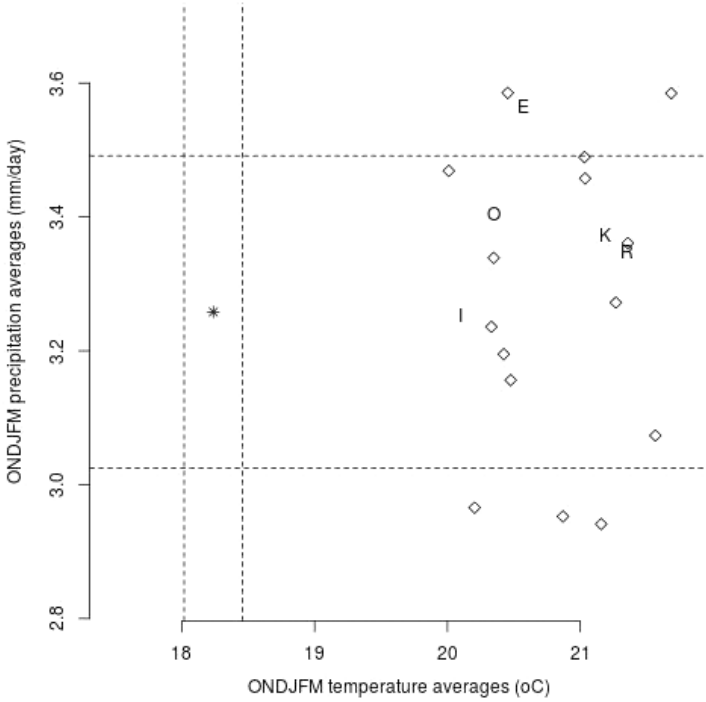


Fig. 6. Mean summer (ONDJFM) temperature and precipitation projected by 20 CMIP5 GCMs (denoted by diamond shapes and letters E, I, K, O, and R for the five GCMs used in the integrated assessment) for Bethlehem in the 2050s under the high-emissions RCP8.5 scenario. The star represents the current conditions. The vertical and horizontal dashed lines indicate the boundaries of statistical significant deviation expected from the 31-year baseline period for temperature and rainfall, vertically and horizontally respectively.

micro-climate, typical terrain morphology, and characteristic soil-distribution pattern in the landscape. The original land-type database with a spatial reference to polygons was modified to a spatial land-type database based on a 90 m STRM (NASA Shuttle Radar Topographic Mission) digital elevation model (Gorokhovich and Voustianiouk, 2006), which was used to identify the location and distribution of four terrain units within each land type by using relative elevation and inflection points along an S-shaped slope profile to classify the terrain units (Zerizghy *et al.*, 2013). The soil properties required for crop modeling using DSSAT and APSIM were derived by using the identified soil series suitable for maize production within each terrain unit. The soil properties for each field were first calculated for each terrain unit to determine the weighted averages of the soil properties. The soil properties for each field were calculated based on the percentage representation of each terrain unit within a field by using zonal statistics. This resulted in each field having a unique soil description.

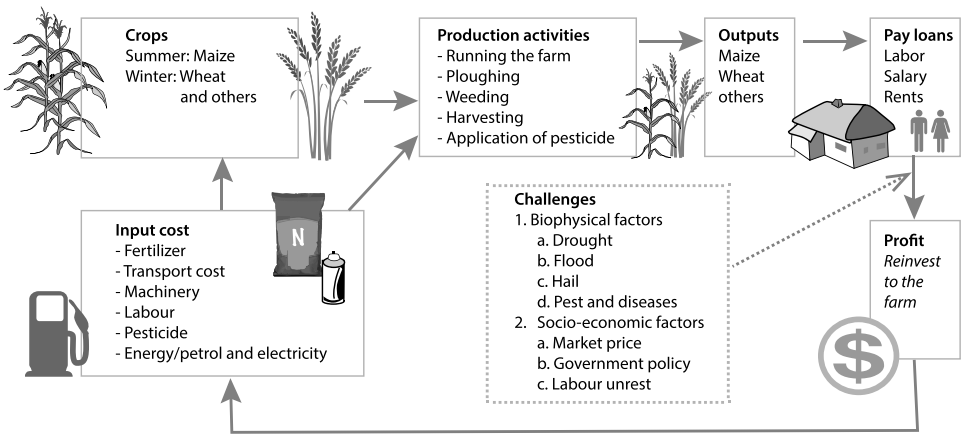


Fig. 7. Schematic diagram of different activities and challenges that affect the commercial farming system in Bethlehem.

Large-scale commercial farming system

Linkages and interactions between different activities in a commercial farming system in Bethlehem are indicated in Fig. 7. Farmers plant maize and wheat under dry land and irrigated conditions, and strive to increase their productivity for profitable enterprises. The farming system involves inputs such as rain, irrigation, fertilizer, and human inputs such as labor and production activities, to turn the inputs to outputs. The farmers reinvest back to their fields, buying machinery and education for their children from their profit generated from sale of produce after paying their loans, labor, salary, and rents. Biophysical and socio-economic conditions influence the farming system productivities.

Although crop simulations were done only for maize, for the analysis of the complete farming system in Bethlehem, the economic analysis considered other important food crops in the study area. Based on secondary data review and expert advice, wheat was identified as the other main important crop. Additional crops grown in the study area were grouped as other crops.

Stakeholder Interactions, Meetings, and Representative Agricultural Pathways

Stakeholder interactions and meetings

Agriculture is a complex sector in which biological, economic, policy, and social factors interact to determine farmers' production each season. In order to understand how policy and social factors are important agricultural drivers, a stakeholders'

meeting was held on 28 June, 2013, in Namibia. Farmers, farmer unions' representatives, economists, and agriculture experts were invited to the meeting. Since each country within the Southern Africa region (Fig. 1) has its own specific set of policy and social interactions, the interaction with the stakeholders continued after this first international meeting on a country-by-county basis. The scientists in a given country interacted with their own local stakeholders, which resulted in a number of such interactions as shown in Table 1.

Representative agricultural pathways (RAPs)

Representative agricultural pathways (RAPs) are qualitative storylines that can be translated into economic model parameters such as farm and household size, costs of production, prices, and policy (Antle *et al.*, 2014; Claessens *et al.*, 2012; Valdivia *et al.*, 2012, 2014). RAPs developed by AgMIP (Rosenzweig *et al.*, 2013; Valdivia *et al.*, 2014) are consistent with new scenario concepts being developed by the international climate modeling and impact assessment communities with inputs from stakeholders. Methods developed by Antle (2014) were used to build the RAPs for each country in Southern Africa.

Data and Methods of Study

Climate

Observed trends in temperature and precipitation

Out of a number of weather recording stations over the Free State, three were used for the baseline according to their proximity to the study sites, length of records, and data quality. For the case study presented here, the Bethlehem historical records were used, latitude = –29.10, longitude = 26.30, altitude = 1353 m. The daily minimum and maximum temperatures, as well as daily rainfall amounts, were extracted from the Climate System Analysis Group, University of Cape Town records.[1] The historical records included missing data that had to be filled in to comply with crop model requirements. This operation has been performed according to AgMIP standards, which consist of using AgMERRA data where necessary (Ruane *et al.*, 2014). Given the quality of the original station records, it was decided to compute solar radiation (for DSSAT) and potential evapotranspiration (for APSIM) according to the Allen *et al.* (1998) approach. Homogeneous climate areas were defined, and

[1] Original data obtained from the Computing Centre for Water Research (CCWR) and the South African Weather Service (SAWS).

farm-specific daily climate datasets were computed by geographical bias correction (relying on the WorldClim dataset obtained from www.worldclim.org).

Significance tests for delta method changes

The AgMIP global climate team uses lower and upper significance thresholds computed at each station, relying on the 31-year baseline period (see Part 1, Chapter 3 in this volume). This bandwidth is used to categorize separately future temperature and rainfall projections that remain within expected statistical deviation, as opposed to those that change beyond the expected deviation, hence suggesting a climate change beyond natural variability.

The significant change amplitude is computed as 0.36 of the standard deviation of the monthly (growing season only) averages over the 31 years. This amplitude subtracted and added to the average gives respectively the lower and upper limits of significant change and are plotted as dashed horizontal (rainfall) and vertical (temperature) dashed lines in Fig. 8.

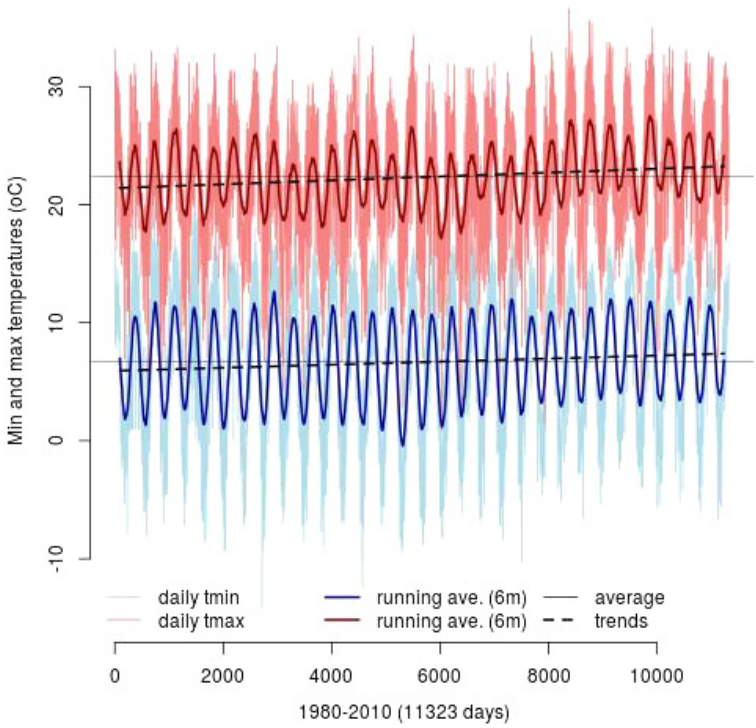


Fig. 8. Minimum and maximum temperatures baseline trends for Bethlehem. Both minima and maxima show an increasing trend over 1980–2010 (approx. 0.5°C per decade).

Climate projections

At each location, changes from the current climate (1980–2010) to near-future (2010–2040), mid-century (2040–2070), and end-of-century (2070–2100) were computed for RCP4.5 and RCP8.5 (Moss *et al.*, 2010). The RCPs describe the forcing effects of atmospheric greenhouse gases (GHGs) to 2100 (Taylor *et al*., 2012). Twenty GCMs were used to compute 20 delta changes in monthly temperatures and monthly rainfalls, hence producing 20 future weather scenarios per baseline. Each dataset was made available as a standard *.AgMIP format, which can be translated automatically into DSSAT and APSIM formats through the QuadUI AgMIP tool (downloaded from http://research.agmip.org/display/dev/QuadUI). For this study, RCP8.5 was selected, representing the highest emission scenario. A corresponding CO_2 level of 571 ppm was used when simulating crop response for the mid-century. A CO_2 level of 360 ppm was used when simulating the baseline period (1980–2010).

Crops

Since field household survey data were unavailable for each maize field, crop management factors such as planting density and row width were obtained from the yield survey of the Free State (Statistics South Africa, 2011) and associated with the fields proportionally to their occurrence. Fertilizer rates were based on average calculated yields for each field by using 50-year historic climate data (1950–1999) at a rate of 1.5 kg nitrogen (N) per hectare for each ton of grain produced. Fertilization application rates were based on soil description, crop withdrawal (i.e., nitrogen use), and commercially accepted norms for the region. On this basis, nitrogen fertilization applications ranged from N: 80 to 120 kg/ha and phosphorus (P): 40 to 50 kg/ha. Fertilization and plant population density guidelines used by the farming communities in the district were also taken into account (personal communications with SENWES Coop (cooperative) and Fertilizer Distributors, South Africa).

Crop model calibration (*DSSAT and APSIM*)

DSSAT and APSIM were run using the agronomic variables: Row width, planting population, fertilizer application, and planting window. The management practices were assigned to the field as a percentage of fields that adopted a given management (Tables 2 and 3). Information about the proportion of the management practices was obtained by analyzing five years of objective yield surveys of the Free State (ARC GCI, 2013). In general, the planting window was between 30 September and 30 December, row width between 75–280 cm and 92–150 cm, plant population 0.5 and 5.5 plants/m^2, and fertilizer 20 and 89 kg N/ha.

Table 2. Row width, plant population, and planting window, and corresponding total coverage in the 400 simulated fields.

Row width (cm)	Percentage of total fields (400 fields)	Plant population (plants/m^2)	Percentage of total fields (400 fields)	Planting window (date)	Percentage of total fields (400 fields)
75	0.5	0.5	1	30/9	2
92	25.8	1.0	6	10/10	5
100	12.3	1.5	18	20/10	3
120	7.3	2.0	33	31/10	11
150	28.5	2.5	18	10/11	16
180	15	3.0	15	20/11	31
210	2.8	3.5	5	30/11	17
250	3.8	4.0	2	10/12	12
280	0.5	4.5	3	20/12	5
		5.5	1	30/12	1

Table 3. Fertilizer applied and the corresponding coverage of the 400 simulated fields.

Fertilizer applied (kg/ha)	20–30	31–40	41–50	51–60	61–70	71–80	81–90
% of total fields (400 fields)	4	17	23	35	15	5	3

The maize models were calibrated in the study area with a range of field experiments by Du Toit (1992, 1996), and Du Toit *et al.* (1994a–c, 1997, and 1998). These datasets (which represent different locations, varieties, plant densities, planting dates, row widths, years, and management regimes for model calibration) are documented by Du Toit (1996). In this study, the genetic coefficients (PAN6479) as determined by Du Toit (1996) for CERES-MAIZE in DSSAT v 3.0 were used as coefficients for both DSSAT v4.5 and APSIM v7.4. The translation of the genetic coefficients from DSSAT v3.0 and v4.5 was done by following the set of formulae provided the new DSSAT v4.5 *.CUL file for maize (Hoogenboom *et al.*, 2012). The genetic coefficients for maize in APSIM v7.4 were derived in the same way using the experimental work of Dimes and Du Toit (2009) and Ncube *et al.* (2007, 2009). The genetic coefficients for the maize genotypes used are presented in Table 4b. The PI, P2, G2, G3, and P5 values are considered to represent PAN6479 in South Africa.

The soils were selected according to the land types, which include the definition of key soil elements such as soil-layer depth, soil water content at air dry, drained upper limit, saturation water content, lower limit of the plant extraction, daily drainage coefficient, and bulk density. The soil nutrition parameterization was also described based on the soil organic carbon and nitrogen levels. For soil carbon

Table 4a. Genetic coefficients for the maize variety, PAN6479 used in the DSSAT crop model.

Crop model	Cultivar name	P1	P2	P5	G2	G3	Phint
DSSAT	PAN6479	200	0.6	710	500	8.5	38.9

P1 = Cumulative daily temperatures from seedling emergence to the end of the juvenile phase.
P2 = Photoperiod sensitivity coefficient (days/h).
P5 = Cumulative daily temperatures from silking to physiological maturity (°C).
G2 = Maximum kernel number (kernels/plant).
G3 = Potential kernel growth rate (mg/kernel/day).
Phint = Phyllochron interval. The interval in thermal time between successive leaftip appearances.

Table 4b. Genetic coefficients for the maize variety, PAN6479 used in the APSIM crop model.

Crop parameters	APSIM inputs (cultivar PAN6479)
End of juvenile stage to initiation	20
Emergence to end of juvenile (P1)	200 (°C day)
Flowering to maturity	500 (°C day)
Grain growth rate	9 mg/grain/day
Flag to flowering	10 (°C day)
Flowering to grain-filling	170 (°C day)

availability the CENTURY model was used for DSSAT. The organic soil carbon is very low (2–4%) in South Africa as they have been cultivated over a long period (Mills and Fey, 2004). The soil water content was reset at the beginning of each season from the information obtained from the land-type dataset.

For this set of simulations, a medium-maturing maize hybrid (PAN6479) was selected; although it is not a new hybrid, it is commonly grown under semi-arid conditions. The crop models were evaluated using district-level observed data for large-scale farmers for 18 years of recorded yields (1981–1999). The crop models were run for each field using associated agronomic management practices: Planting dates, plant populations, and nitrogen fertilizer rates (Tables 2 and 3). The root mean square error (RMSE) between observed and simulated yield is calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}(y_i - \hat{y}_i)^2} \tag{1}$$

where y_i are the measurements, $\hat{y}_i$ the simulations, and n is the number of comparisons.

Table 5. GCMs used and corresponding identification letters (see Part 1, Chapter 3 in this volume for more details).

GCM ID	GCM	GCM source
A	ACCESS1.0	CSIRO (Commonwealth Scientific and Industrial Research Organisation) and BOM (Bureau of Meteorology), Australia
B	BCC-CSM1.1(m)	Beijing Climate Center, China Meteorological Administration
C	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University
D	CanESM2	Canadian Centre for Climate Modeling and Analysis
E	CCSM4	National Center for Atmospheric Research, USA
F	CESM1(BGC)	National Science Foundation, Department of Energy, National Center for Atmospheric Research, USA
G	CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence
H	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, USA
I	GFDL_ESM2	NOAA Geophysical Fluid Dynamics Laboratory, USA
J	HadGEM2-CC	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)
K	HADGEM2_ES	Met. Office Hadley Centre, UK
L	INM-CM4	Institute for Numerical Mathematics
M	IPSL-CM5A-LR	Institut Pierre-Simon Laplace
N	IPSL-CM5A-MR	Institut Pierre-Simon Laplace
O	MICROC5	Atmosphere and Ocean Research Institute, the University of Tokyo
P	MIROC-ESM	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
Q	MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M)
R	MPI_ESM_MR	Max Planck Institute for Meteorology, Germany
S	MRI-CGCM3	Meteorological Research Institute
T	NorESM1-M	Norwegian Climate Centre, Norway

Past and future crop productivity and yield variability were simulated for each field with baseline (1980–2009) and future (2040–2070) climate scenarios, with the latter created by using the data methods with weather data changes computed from the 20 GCMs (Table 5).

The relative yield for each field is then provided to the economists as input to run TOA-MD. The relative yield change was calculated as follows:

$$RY = \frac{\hat{Y}_f}{\hat{Y}_b} \tag{2}$$

where $\hat{Y}_f$ is the average of the 30-year simulated yield using the GCMs future climate scenarios, and $\hat{Y}_b$ is the average of the 30-year simulated yield using baseline weather.

The boxplots (Fig. 8) show the distribution of responses from both crop models to baseline weather and different GCMs. The horizontal line in each box represents the median response; the box delimits the 25th to 75th percentiles; and the whiskers

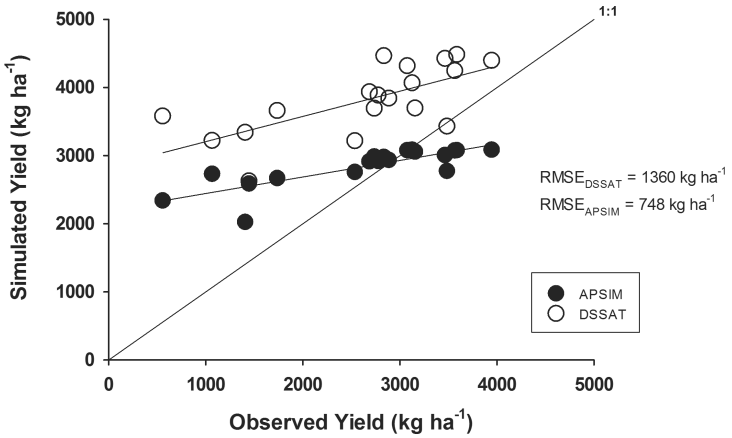


Fig. 9. Observed Bethlehem yield and simulated maize yield for PAN6479 cultivar.

range from the 10th to the 90th percentiles. The simulated outputs by the two crop models were used to generate a probability distribution of yield for each baseline GCM and each field, averaged over 30 years of weather data. The coefficient of variability (CV%) of the average (30 years) yield data between different farms was calculated as follows:

$$CV = \frac{\sigma}{\mu} 100 \tag{3}$$

where σ is the standard deviation across simulated yield between farms and μ is the average of the 30 years of simulations for both crop models.

Model evaluation

DSSAT has been calibrated for maize, under local conditions and it was also evaluated against results obtained from field data in South Africa (Du Toit, 1992, 1996; Du Toit and Prinsloo, 2000; Du Toit *et al.*, 1994a–c, 1997, 1998). APSIM has also been calibrated and evaluated for different varieties and management practices in Southern Africa (Dimes and Du Toit, 2009; Ncube *et al.*, 2007, 2009). The evaluation of the two models is shown in Fig. 9. Overall, APSIM and DSSAT tend to overestimate maize yield, especially at lower yields. The RMSE is 1360 and 748 kg/ha for DSSAT and APSIM, respectively (Fig. 10). However, the hybrid used in this study was a common hybrid in the mid-1990s, while the observed data are from 1981. From the 1980s onwards, there has been a recorded yield increase because of new hybrid availability, as well as better management techniques including increased fertilization and higher-density planting techniques. In addition, the maize crop was well calibrated for detailed field experiments, but this evaluation is at district level, so this represents a different (i.e., aggregated) scale.

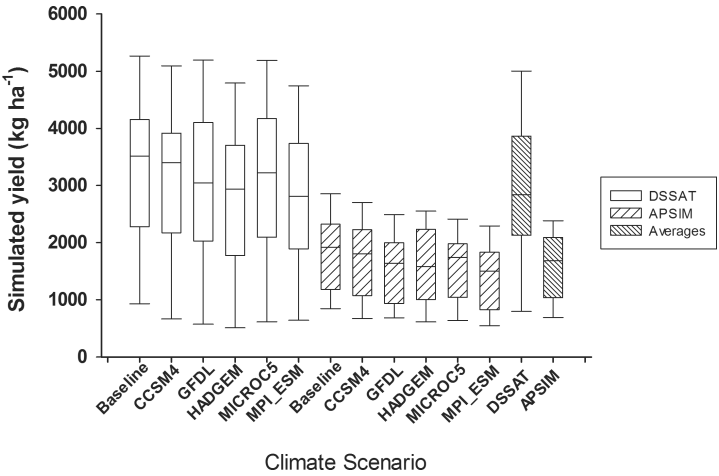


Fig. 10. Interannual variability of the simulated maize yield for 400 fields in Bethlehem for DSSAT and APSIM and five GCMs (CCSM4, GFDL_ESM2, HADGEM2_ES, MIROC5, and MPI_ESM). In each boxplot horizontal lines from the top to the bottom represent the 90th, 75th, 25th, and 10th percentiles; the line represents the median value.

Economics

TOA-MD (Antle, 2011; Antle and Valdivia, 2006; Antle *et al.*, 2014) was used to assess the impacts of climate change and adaptation on agricultural production systems focusing on commercial maize production systems in Bethlehem. The socio-economic data for the district were obtained from the Census for Commercial Agriculture for the Free State province (Statistics South Africa, 2011) and Department of Agriculture, Forestry and Fishery (DAFF) survey data. The socio-economic data includes household characteristics, crop productions (crop yields/quantities and prices); on the input side (that includes seeds, labor, fertilizer, and manure), and land area under cultivation were obtained from DAFF. Data from Grain SA (2012) were used to calculate net returns (mean and standard deviation) for the maize crop production in each farm (as indicated in Table 6), which are spread heterogeneously across the district.

The economic analysis of climate change impacts on crop production in Bethlehem focused on three main research questions used for the AgMIP project: (1) What is the sensitivity of current agricultural production systems to climate change? (2) What is the impact of climate change on future agricultural production systems? (3) What are the benefits of climate change adaptations? Preliminary results are presented in the discussion below.

Crop modeling data for maize were obtained from crop scientists based on two crop models, APSIM and DSSAT. The crop modeling data represented

Table 6. Data used for economic analysis. The standard deviations are reported in parentheses.

Variable	Baseline mean (s.d.)
Mean maize yield (kg/ha)	2993 (869.91)
Net returns (R/farm)	2 546 967 (1 061 747)
Variable cost (R/ farm)	1 562 168 (161 992)
Farm size (ha)	641.50

Table 7. Analysis of the proportion of area, production, and revenue from the main crops grown in Bethlehem.

	Field size		Production			Revenue	
Crop	Area (ha)	Proportion in relation to maize	Production	Productivity (kg/ha)	Proportion in relation to maize	Revenue R'000	Proportion in relation to maize
Maize	37691	1.00	112818	2993	1.00	139031	1.00
Wheat	29654	0.79	74354	2507	0.84	122500	0.88
Sunflower	4854	0.13	6126	1262	0.42	13305	0.10
Dry beans	4703	0.12	7188	1528	0.51	29937	0.22
Soya beans	2482	0.07	3897	1570	0.52	8225	0.06
Sorghum	585	0.02	727	1242	0.42	1174	0.01
Groundnuts	227	0.01	305	1343	0.45	1441	0.01
Total	**80196**		**205415**			**315613**	

Source: Statistics South Africa (2007) Free State province census of commercial agriculture.

simulated maize production under five different GCMs (CCSM4, GFDL_ESM2, HADGEM2_ES, MICROS5, and MPI_ESM_MR) for both crop models.

Table 7 summarizes the secondary data analysis on the proportions of farm production of the main food crops grown in Bethlehem compared to maize using data from the last provincial Census of commercial agriculture for the Free State by Statistics South Africa. To have a complete farming system analysis for Bethlehem, the proportions in Table 7 were used to estimate future production, revenue, and production costs for these crops based on simulated maize data. The TOA analysis focused on maize and wheat as the main crops and aggregated the rest as "other crops". The 2007 data for maize were also used to normalize simulated data from crop modeling.

For poverty analysis, South Africa has three definitions: (1) Food poverty line: R305 (in March 2009 figures) *per capita* per month, i.e., R3660 *per capita* per year (1US$ = ~R10); (2) lower-bound poverty line: R416 (in March 2009 figures) *per capita* per month, i.e., R4992 *per capita* per year; and (3) upper-bound poverty line: R577 (in March 2009 figures) *per capita* per month, i.e., R6924 *per capita* per year

Table 8. The changes in farm size, maize price, variable costs, and productivity growth due to technology change under RAP1.

Variable	RAP1	Description
Farm size	85%	Commercial farms are expected to reduce in size by 15% as more land is taken for land restitution and land reform.
Maize price	110%	Maize output price is expected to increase by 10%.
Variable cost/ ha	120%	Variable costs are expected to increase by 20%.
Productivity growth due to technology change	105%	Adoption on changed technology is expected to improve yields by 5%.

Table 9. Field-level adaptation package used for the district.

Adaptation package	Future expected changes
Fertilizer application	Increase by 30%.
Maize varieties	A change in cultivar from a medium to long season varieties.

(Statistics South Africa, 2012). The empirical findings presented in this paper were based on the upper-bound poverty line. This poverty line was selected based on the focus on commercial agricultural for this study, which has relatively higher income levels compared to subsistence farming. This is different from other AgMIP studies that have used $1.25/day/person as the poverty line.

RAP narrative and development

One RAP scenario was developed for South Africa: RAP 1 — Low Adaptation Challenges: South Africa will follow a more positive economic development pathway in line with the National Development Plan, Vision 2030 (National Planning Commission, 2012), characterized by higher rates of economic growth, increased agricultural technology development and use, and increased access to productive commercial agricultural land. Increased investments in implementing agricultural and land-reform policies provide a positive environment for increased agricultural production of commodities such as maize. Improved economic performance and associated reductions in poverty enhance social cohesion and facilitate investments in commercial agriculture production such as maize production (20% increase in variable costs; 10% increase in output price; 15% decrease in farm size and 5% increase in productivity growth due to technology change; see Table 8).

Adaptation package

A simple adaptation package was tested by changing one element at a time under baseline and future climate scenarios. The packages that best mitigate the effect of climate change on the production of maize were selected (Table 9).

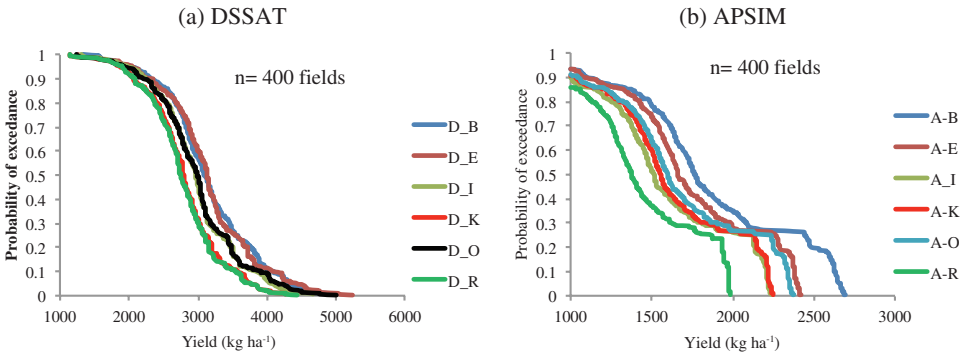


Fig. 11. Probability of exceedance plots showing climate effects on maize yields simulated by the (a) DSSAT and (b) APSIM crop models. Lines represent the 30-year mean simulated yield for each field, for the baseline and five GCMs. Spatial variability is reflected in these plots.

Core Question 1: What is the Sensitivity of Current Agricultural Production Systems to Climate Change?[2]

Impact of climate change on crop production

The average simulated maize grain yield for commercial farmers for the baseline time-period (1980–2010) was 3155 kg/ha with CV of 49% between farmers. These results are within the norm of what commercial farmers are expected to harvest (GrainSA, 2013). The five GCM climate scenarios have been simulated using the DSSAT and APSIM crop models for the 2050s (2040–2070) time-period. DSSAT and APSIM both simulated a decline in yield, projecting similar responses to climate change. Both models simulated a lower yield for the five GCMs relative to the simulated baseline, which is an indication of yield losses with the projected climate change. The APSIM model estimated lower yields in all cases compared with DSSAT (Fig. 10). The variability of yield simulated by APSIM was relatively lower than that of DSSAT, and APSIM yield projections also differentiated among the GCMs more noticeably than those simulated by DSSAT, especially the GDFL, HADGEM2, and MPI_ESM scenarios. Overall, the simulated median yield decline is estimated to be about 10% and 16% with DSSAT and APSIM, respectively. This means that climate change is projected to affect the farming sector negatively if the farmers in this district continue to use current management practices.

Figure 11 shows variation of simulated maize yield due to the spatial variability of tested fields. The mean yield of all the fields simulated by DSSAT is greater than 1000 kg/ha over a period of 30 years for all the scenarios, whereas mean yield simulated by APSIM showed 10% of the fields would produce less than 1000 kg/ha.

[2]Preliminary results.

Both models displayed a range of results that could occur due to agronomic practices, soils, and weather across the 400 fields.

Economic impact of climate change on current production systems

DSSAT and APSIM simulated maize yield outputs under five climate change scenarios were used to simulate climate change impacts on the socio-economic conditions in the district by using the TOA-MD model.

Table 10 presents the sensitivity of current production systems to climate change. The results show that current crop production systems in Bethlehem are adversely affected by changes in climate. Yield and net revenues per hectare decrease by 9% to 28% as a result of changes in climate. Furthermore, the results show that the percentage of losers ranges from 62% to 78% and all GCMs show negative net impact (that is the sum of the gains and losses due to climate change, ranging from −7% to −15% mean net returns) on crop production systems in Bethlehem. The gains mean that farmers get positive net returns per farm with climate change and vice versa. The results for welfare indicators show that *per capita* income generally decreases with future climate change by between 10% and 27% from current levels while there are marginal increases in poverty rates of between 2% and 3%. Overall, the analysis shows that current crop production systems are vulnerable to future changes in climate. The findings are supported by earlier empirical studies (Gbetibouo and Hassan, 2005), which found that agricultural production systems in South Africa are vulnerable to climate change impacts.

Core Question 2: What is the Impact of Climate Change on Future Agricultural Production Systems?[3]

Results and discussion

This section discusses the climate change impacts on future crop production with assumptions described in RAP1 in Bethlehem. The analysis and discussion focus on understanding how predicted changes in climate from different climate models might affect projected production of main crops (maize, wheat, and other crops) with future changes in farm size, maize prices, fixed and variable costs, and technology changes described in RAP 1 without adaptation.

The trends used for the future maize price and yield were based on the AgMIP reference from the IMPACT model. Based on the IMPACT model, maize price increased by 40% from the observed value while maize yield increased by 22%. Changes in other variables such as variable costs and farm size were elaborated

[3]Preliminary results.

Table 10. Sensitivity of current agricultural production systems to climate change. Preliminary results.

	C1 — CCSM4		C2 — GFDL_ESM2		C3 — HADGEM2_ES		C4 — MICRO5		C5 — MPI_ESM_MR	
	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT
Observed mean yield (maize) (kg/ha)*	2993	2993	2993	2993	2993	2993	2993	2993	2993	2993
Mean yield change (maize) (%)**	−13.00	−9.00	−17.00	−12.00	−21.00	−14.00	−11.00	−11.00	−28.00	−18.00
Losers (%)	64.98	61.83	70.02	62.91	72.17	71.89	64.41	63.10	78.19	71.90
Gains (% mean net returns)	22.04	22.50	20.98	22.22	20.66	14.76	22.17	22.17	19.99	19.36
Losses (% mean net returns)	−31.27	−29.60	−33.79	−29.98	−35.15	−24.94	−31.02	−30.06	−34.79	−32.77
Observed net returns without climate change (ZAR/ha)	2840876	2881311	2840876	2881311	2840876	2881311	2840876	2881311	2840876	2881311
Observed net returns with climate change (ZAR/ha)	2482976	2601618	2347361	2575363	2283284	2484111	2497348	2570617	2068280	2359245
Observed *per capita* income without climate change (ZAR/Person/Year)	858401	870557	858401	870557	858401	870557	858401	870557	858401	870557
Observed *per capita* income with climate change (ZAR/Person/Year)	750807	786474	710038	778581	690775	751148	755128	777154	626139	713611
Observed poverty rate without climate change (%)***	8.56	8.34	8.56	8.34	8.56	8.34	8.56	8.34	8.56	8.34
Observed poverty rate with climate change (%)***	8.70	8.53	8.73	8.49	8.72	8.55	8.72	8.50	8.78	8.55

Note:
*Normalized.
**Defined as: (mean relative yield–1)× 100.
***Poverty line: Upper-bound poverty line (R577) *per capita* per month or (R6924) *per capita* per year. Exchange Rate: 1USD = R10
C = climate model, M = crop model.

from RAPs. Table 11 shows impacts of future climate change on future production systems for Bethlehem. The results show that the percentage of losers from climate change ranges from 53% to 77%. Future changes in climate adversely affects future production systems in Bethlehem with yield and net revenue losses ranging from −3% to −27% per farm. In addition, future production systems in Bethlehem are expected to experience net negative impacts as a result of climate change ranging from −2% to −20%. Empirical results on agricultural systems in Africa by Dinar *et al*. (2008) Nhemachena (2009), and Nhemachena *et al*. (2010) also showed that specialized crop farms (such as the commercial production in Bethlehem) would be most affected by projected changes in climate. Findings from these studies showed that highly specialized crop or livestock farms are less adapted to changes in climate and more vulnerable compared to the dominant mixed crop-livestock farms in most parts of Africa. Further evidence by Kiker (2002) indicates that parts of Free State province are located in parts of the marginal areas that would become unsuitable for maize production as a result of climate change.

The welfare variables (PCI (*per capita* index) and poverty) also show that climate change will adversely affect livelihoods in Bethlehem. Poverty is expected to increase by between 1% and 3% and PCI to decrease by 5% and 27%. This implies that although climate change results in decreases in crop yields, there are other factors that might be contributing to decreases in poverty such as improved income from alternative sources outside agriculture as well as better future prices and improved technology. In addition, the interaction of climate change with other natural and socio-economic variables such as water scarcity, decreasing soil fertility, reduction of farm sizes due to land reform etc., will worsen the impacts on crop production systems in Bethlehem and throughout the Free State province. Clearly, without any adaptation, crop production will be adversely affected and the impacts would affect food security in the country as well as progress made by efforts aimed at reducing poverty and food insecurity.

Core Question 3: What Are the Benefits of Climate Change Adaptations?[4]

Impact of adaptation on crop productivity

Table 12 shows the impacts of adoption of climate change adaptations on future crop production systems in Bethlehem. The adaptation package analyzed for this study included the introduction and adoption of an improved long-season maize seed variety and different levels of fertilizer application by 30%. The results show that with adaptation, crops yields per hectare will increase by between 13% and 22%. Crop modeling simulation results that incorporate the adaptation together with the

[4]Preliminary results.

Table 11. The impact of climate change on future agricultural production systems in Bethlehem. Preliminary results.

	C1 — CCSM4		C2 — GFDL_ESM2		C3 — HADGEM2_ES		C4 — MICRO5		C5 — MPI_ESM_MR	
	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT
Projected mean yield (maize) (kg/ha)	3666	3666	3666	3666	3666	3666	3666	3666	3666	3666
Mean yield change (maize) (%)*	−13.00	−9.00	−17.00	−12.00	−21.00	−14.00	−11.00	−11.00	−28.00	−18.00
Losers (%)	60.85	53.39	66.44	61.88	69.92	62.92	59.95	57.89	76.84	73.61
Gains (% mean net returns)	24.37	25.64	22.97	18.00	22.31	22.71	24.62	17.22	21.42	17.66
Losses (% mean net returns)	−31.31	−27.72	−33.77	−23.71	−35.83	−30.64	−31.01	−20.64	−41.61	−31.26
Projected net returns without climate change (ZAR/ha)	2835306	2898826	2835306	2898826	2835306	2898826	2835306	2898826	2835306	2898826
Projected net returns with climate change (ZAR/ha)	2565665	2816379	2417599	2672572	2315343	2583905	2587581	2762676	2069613	2366795
Projected *per capita* income without climate change (ZAR/Person/Year)	816553	834740	816553	834740	816553	834740	816553	834740	816553	834740
Projected *per capita* income with climate change (ZAR/Person/Year)	739352	811134	696960	769961	667683	744575	745627	795758	597328	682414
Projected poverty rate without climate change (%)**	9.43	8.66	9.43	8.66	9.43	8.66	9.43	8.66	9.43	8.66
Projected poverty rate with climate change (%)**	9.49	8.71	9.51	8.69	9.48	8.71	9.52	8.72	9.68	8.68

Note:
*Defined as: (mean relative yield–1)× 100.
**Poverty line: Upper-bound poverty line (R577) *per capita* per month or (R6924) *per capita* per year. Exchange Rate: 1USD = R10
C = climate model, M = crop model.

Table 12. The potential benefits of climate change adaptations to future agricultural production systems. Preliminary results.

	C1 — CCSM4		C2 — GFDL_ESM2		C3 — HADGEM2_ES		C4 — MICRO5		C5 — MPI_ESM_MR	
Stratum 1	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT	M1 — APSIM	M2 — DSSAT
Projected mean yield without adaptation (maize) (kg/ha)	2762	2925	2660	2829	2497	2782	2878	2864	2273	2617
Mean yield change (maize) (%)*	20	22	16	15	20	15	21	19	15	13
Percentage adoption rate	61.68	62.60	62.97	63.13	69.28	62.52	69.79	61.32	69.38	63.60
Projected net returns without adaptation (ZAR/ha)	2474622	2753957	2327600	2614889	2230247	2526919	2490455	2700969	1988000	2317337
Projected net returns with adaptation (ZAR/ha)	2866069	3344977	2869721	3187673	2705078	2941680	3036110	3252427	2406128	2676508
Projected *per capita* income without adaptation (ZAR/Person/Year)	713286	793262	671192	753446	643319	728259	717819	778091	573961	668254
Projected *per capita* income with adaptation (ZAR/Person/Year)	825361	962477	826407	917439	779268	847009	874045	935979	693675	771088
Projected poverty rate without adaptation (%)**	9.03	8.45	9.15	8.44	9.12	8.45	9.16	8.45	9.31	8.43
Projected poverty rate with adaptation (%)**	7.92	6.59	7.24	6.59	8.07	7.05	8.13	6.58	8.1	7.17

Note:
*Defined as: (mean relative yield–1) × 100.
**Poverty line: Upper-bound poverty line (R577) *per capita* per month or (R6924) *per capita* per year. Exchange Rate: 1USD = R10
C = climate model, M = crop model.

RAP described above were used to estimate the impacts of adaptation on crop production in Bethlehem. The results also show adoption rates ranging from 61% to 69% of the adapted crop production system under climate change. In addition, net returns per hectare will increase by 12% to 18% with adaptation.

Impact of adaptation on farmers' livelihoods

PCI increases from between 15% and 23% with the adoption of the adaptation package. Furthermore, the adaptation package analyzed in this study shows that poverty levels decrease by 12% to 22%. Generally, the adoption of the adaptation package helps to reduce the negative impacts of climate change of crop production systems. However, further analysis would be required to test different adaptation packages and RAPs on future crop production systems in Bethlehem. It is important to note that in addition to adaptation, the positive RAP scenario presented for this analysis will also contribute to improve crop productivity in the face of climate change. For example, increased government support for development of improved agricultural technologies, extension and other support will contribute to increased use of improved technologies such as adaptation strategies. All these will contribute to the reduction of the impacts of climate change. An analysis of RAP with lower development conditions (i.e. a more pessimistic future) could be an interesting extension for this analysis.

Conclusions and Next Steps

Projections of future changes in climate for South Africa showed an increase in temperature together with increased variability in rainfall, thus increasing the risk of crop failure and food insecurity in the region. The overall results from the two crop models (DSSAT and APSIM) using five different climate scenarios show that current maize production in Bethlehem would be substantially affected by climate change without any adaptation. These results imply that maize production will be lowered by 10% to 16% due to changes in climate in the future.

The TOA analysis results show that current agricultural production systems in Bethlehem are sensitive to climate change with net returns per hectare and PCI also adversely affected. Furthermore, the percentage of losers ranges from 62% to 78% and all GCMs show negative net impact (ranging from –7% to –15%) on crop production systems. Poverty levels increases in current production systems from 2% to 3%. Overall, the analysis shows that current crop production systems are vulnerable to future changes in climate. In addition, results on the impact of climate change on future agricultural production systems indicate that future systems are also affected by future changes in climate. About 53% to 77% of farmers will lose

from changes in climate in the future. As with current production systems, future systems will be adversely affected if no adaptation measures are implemented.

Analysis of the benefits of adoption of the adaptation package show positive gains in yields per hectare; net returns ranging from 11% to 20% compared to the scenario without climate change adaptation. The results also show adoption rates ranging from 61% to 69% of the adapted crop production system under climate change. Furthermore, with adaptation, poverty levels decrease by between 12% and 22%. Other factors presented in the RAP scenarios such as increased government support for development of improved agricultural technologies and extension will contribute to increased use of adaptation strategies. Generally, the results show that implementing adaptation measures, as well as other supporting strategies like those mentioned above, will enhance productivity of crop production systems and reduce predicted impacts due to climate change.

In this phase of the AgMIP project, skills of scientists were enhanced to perform detailed technical analysis in the areas of climate analysis, crop modeling, economics, and stakeholder engagement. Integrated climate change impact analyses need to expand to different sites, time-slices, crops, and cropping systems in the region to support future planing for the agriculture sector.

References

Agricultural Research Council and Land Type Survey Staff (2006). *Land types of South Africa: Digital map (1:250 000 scale)* and soil inventory datasets, Agricultural Research Council, Institute for Soil, Climate and Water, Pretoria.

Akpalu, W., Hassan, R. M., and Ringler, C. (2009). *Climate Variability and Maize Yield in South Africa: Results from GME and MELE Methods*, IFPRI Discussion Paper No. 843, Washington, DC.

Allen, R. G., Pereira, L. S., Raes, D., and Smith, M. (1998). *Crop evapotranspiration — Guidelines for computing crop water requirements*, Irrigation and Drainage Paper no. 56, FAO, Rome.

Antle, J. M. (2011). Parsimonious Multi-Dimensional Impact Assessment, *Am J. Agric Econ*., **93**(5) 1292–1311.

Antle, J. M., Stoorvogel, J. J., and Valdivia, R. O. (2014). New parsimonious simulation methods and tools to assess future food and environmental security of farm populations, *Philos. Trans. R. Soc. Lond. B Biol. Sci.*, **369**(1639), 20120280.

Burke, E. J., Brown S. J., and Christidis, N. (2006). Modeling the Recent Evolution of Global Drought and Projections for the Twenty-First Century with the Hadley Centre Climate Model, *J. Hydrol*., **7**, 1113–1125.

Byerlee, D. and Heisey, P. W. (1997). "Evolution of the African Maize Economy", in Byerlee, D. and Eicher, C. K. (eds.), *Africa's Emerging Maize Revolution*, Lynne Rienner Publishers, Boulder, CO, USA, p. 301.

Challinor, A. J. and Wheeler, T. R. (2008). Crop yield reduction in the tropics under climate change: Process and uncertainities, *Agric. Forest Meteorol.*, **148**, 343–356.

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., and Herrero, M. (2012). A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data, *Agric. Syst.*, **111**, 85–95.

DAFF (Department of Agriculture Forestry and Fishery) (2013). *Maize Market Value Chain Profile*. Available at: http://www.nda.agric.za/doaDev/sideMenu/Marketing/Annual%20Publications/Commodity%20Profiles/field%20crops/Maize%20Market%20Value%20Chain%20 Profile%202013.pdf. Accessed on 12 February 2014.

Davis, C. L. (2011). *Climate Risk and Vulnerability: A Handbook for Southern Africa*. Available at: www.sarva.org.za/sadc/downloads/index.phpý. Accessed on 12 December 2013.

De Wit, M. and Stankiewicz, J. (2006). Changes in water supply across Africa with predicted climate change, *Science*, **311**(5769), 1917–1921.

Dimes, J. P. and Du Toit, P. (2009). "Quantifying water productivity in rainfed cropping systems in Limpopo Province, South Africa", in Humphreys, E. and Bayot, R. S. (eds.), *Increasing the Productivity and Sustainability of Rainfed Cropping Systems of Poor Smallholder Farmers*, Proceedings CGIAR Challenge Program on Water and Food International Workshop on Rainfed Cropping Systems, Tamale, Ghana, 22–25 September, 2008, The CGIAR Challenge Program on Water and Food, Colombo, Sri Lanka.

Dinar, A., Mendelsohn, R., Hassan, R., and Benhin, J. (2008). *Climate Change and Agriculture in Africa: Impacts Assessment and Adaptation Strategies*, Earthscan, London.

Du Toit, A. S. and Prinsloo, M. A. (2000). "Incorporating prolificacy into CERES-Maize prediction of kernel number", in *Physiology and Modelling Kernel Set in Maize* CSSA Special Publication No. 29, Crop Science Society of America and American Society of Agronomy, Madison, USA.

Du Toit, A. S. (1992). *Die invloed van rywydte op die voorspellingswaarde van die CERES-maize mieliegroeisimulasiemodel in die Wes-Transvaal*, unpublished MSc thesis, University of the Orange Free State, South Africa.

Du Toit, A. S. (1996). *The quantification of the compensation ability of the maize plant*, PhD thesis, Department of Agronomy, Faculty of Agriculture, University of the Free State, South Africa.

Du Toit, A. S., Booysen, J., and Human, J. J. (1994a). Evaluation and calibration of CERES-Maize 1. Non-linear regression to determine genetic parameters, *S. Afr. J. Plant Soil*, **11**, 96–100.

Du Toit, A. S., Booysen, J., and Human, J. J. (1994b). Evaluation and calibration of CERES-Maize 2. Phenology prediction values, *S. Afr. J. Plant Soil.*, **11**, 121–125.

Du Toit, A. S., Booysen, J., and Human, J. J. (1994c). Evaluation and calibratin of CERES-Maize 3. Row widths for the western Highveld, *S. Afr. J. Plant Soil.*, **11**, 153–158.

Du Toit, A. S., Booysen, J., and Human, J. J. (1997). Use of linear regression and correlation in the evaluation of CERES3 (Maize), *S. Afr. J. Plant Soil.*, **14**, 177–182.

Du Toit, A. S., Booysen, J., and Human, J. J. (1998). Calibration of CERES3 (Maize) to improve silking date prediction values for South Africa, *S. Afr. J. Plant Soil.*, **15**, 61–66.

Engelbrecht, C. J., Engelbrecht, F. A., and Dyson, L. (2013). High-resolution model-projected changes in mid-tropospheric closed-lows and extreme rainfall events over southern Africa, *Int. J. Climatol*., **33**, 173–187.

Engelbrecht, F. A., McGregor, J. L., and Engelbrecht, C. J. (2009). Dynamics of the conformal-cubic atmospheric model projected climate-change signal over southern Africa, *Int. J. Climatol*., **29** 1013–1033.

Fauchereau, N., Trzaska, S., Rouault M., and Richard, Y. (2003). Rainfall Variability and Changes in southern Africa during the 20th Century in the Global Warming Context, *Nat. Hazards.* **29**, 139–154.

Fischer, G., Shah, M., Tubiello, F. N., and van Velhuizen, H. (2005). Socio-economic and climate change impacts on agriculture: An integrated assessment, 1990–2080, *Phil. Trans. Roy. Soc. B (Biol. Sci.)*, **360**(1463), 2067–2083.

Gbetibouo, G. A. and R. M. Hassan. (2005). Measuring the economic impact of climate change on major South African field crops: A Ricardian approach, *Global and Planetary Change*, **47**, 143–152.

Gorokhovich, Y. and Voustianiouk, A. (2006). Accuracy assessment of the processed SRTM-based elevation data by CGIAR using field data from USA and Thailand and its relation to the terrain characteristics, *Remote Sens. Environ.*, **104**, 409–415.

Grain SA (2012). *Market Reports*. Available at: www.grainsa.co.za. Accessed on 16 October 2013.

Hoogenboom, G., Jones, J. W., Wilkens, P. W, Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J. (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5*. University of Hawaii, Honolulu, Hawaii.

Hulme, M., Doherty, R., Ngara, T., New M., and Lister D. (2001). African Climate Change: 1900–2100 *Clim Res*., **17**(2), 145–168.

IPCC (2007). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L. (eds.), Cambridge University Press, Cambridge.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**, 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**, 267–288.

Kiker, G. A. (2002). "CANEGRO-DSSAT linkages with geographic information systems: applications in climate change research for South Africa", in *Proceedings of International CANEGRO Workshop*, Mount Edgecombe, South Africa.

Kruger, A. C. (2006). Observed trends in daily precipitation indices in South Africa: 1910–2004, *Int. J. Climatol*., **26**, 2275–2286.

Kundhlande, G., Groenewald, D. C., Baiphethi, M. N., Viljoen, M. F., Botha, J. J., Van Rensburg L. D., and Anderson, J. J. (2004). *Socio-economic study on water conservation techniques in semi-arid areas. Report No. 1267/1/04*, Water Research Commission, Pretoria.

Lobell, D., Burke, M., Tebaldi, C., Mastrandera, M., Falco, W., and Naylor, R. (2008). Prioritizing climate change adaptation needs for food security in 2030, *Science*, **319**(5863), 607–610.

Mills, A. J. and Fey, M. V. (2004). Soil carbon and nitrogen in five contrasting biomes of South Africa exposed to different land uses, *South African Plant and Soil.*, **21**(2), 94–102.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

NDA (National Department of Agriculture) (2007). *Census of commercial agriculture, financial and production statistics, 2007.* Available at: www.nda.co.gov. Accesed on 16 October 2013.

Meadows, M. E. (2006). Global change and southern Africa, *Geogr. Res.*, **44**, 135–145.

Nhemachena, C. (2009). *Agriculture and future climate dynamics in Africa: Impacts and adaptation options*, PhD thesis, University of Pretoria, South Africa.

Nhemachena, C., Hassan, R. and Kurukulasuriya, P. (2010). Measuring the economic impact of climate change on African agricultural production systems, *Climate Change Economics*, **1**(01), 33–55.

National Planning Commission (2012). *National Development Plan Vision 2030: Our future make it work*. Available at: http://www.npconline.co.za/. Accessed on 23 July 2013.

Ncube, B., Dimes, J. P., van Wijk, M. T., Twomlow, S. J., and Giller, K. E. (2009). Productivity and residual benefits of grain legumes to sorghum under semi-arid conditions in southwestern

Zimbabwe: Unravelling the effects of water and nitrogen using a simulation model, *Field Crop Res.*, **110**, 173–184.

Ncube, B., Twomlow, S. J., van Wijk, M. T., Dimes, J. P., and Giller, K. E. (2007). Productivity and residual benefits of grain legumes to sorghum under semi-arid conditions in southwestern Zimbabwe, *Plant Soil.*, **299**, 1–15.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorrial G., and Winter J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol.*, 200. doi:10.1016j.agrformet.2014.09.016.

SADC (Southern Africa Development Community) (2013). *Agricultural & Food Security*. Available at: www.sadc.int/themes/agriculture-food-security. Accessed on 25 December 2013.

Schulze, R. E. (2007). *Climate change and the agricultural sector in South Africa: An assessment of findings in the new millennium*, ACRUcons Report 55, School of Bio-resources and Environmental Hydrology Engineering, University of KwaZulu-Natal, Pietermaritzburg.

Schulze, R. E., Meigh J., and Horan M. (2001). Potential and future vulnerability of eastern and southern Africa's hydrology and water resources, *S. Afr. J. Sci.*, **97**, 150–160.

Singels, A., Annandale, J. G., De Jager, J. M., Schulze, R. E., Inman-Bamber, N. G., Durand, W., Van Rensburg, L. D., Van Heerden, P. S., Crosby, C. T., Green, G. C., and Steyn, J. M. (2010). Modelling crop growth and crop water relations in South Africa: Past achievements and lessons for the future, *S. Afr. J. Plant Soil,* **27**(1).

Statistics South Africa (2011). *Poverty Profile of South Africa: Application of poverty lines on the LCS 2008/2009*. Available at: http://www.statssa.gov.za/publications/report-03-10-03/report-03-10-032009.pdf. Accessed on 15 May 2013.

Statistics South Africa (2012). *Agricultural Survey*. Available at: www.statssa.gov.za/agriculture. Accessed on 18 December 2013.

Tadross, M. A., Jack, C. and Hewitson, B. C. (2005). On RCM-based projections of change in southern African summer climate, *Geophys. Res. Lett.*, **32**(23) L23713.

Valdivia, R., Antle, J. M., and Stoorvogel, J. J. (2012). Coupling the Tradeoff Analysis Model with a market equilibrium model to analyze economic and environmental outcomes of agricultural production systems, *Agric. Syst.*, **111**, 85–95.

Van Tol, J. J., Roux, L. E., and Hensley, M. (2012). Pedotransfer function to determine the water conducting macroporosity in South African soils, *Water Sci. Technol.*, **65**(3), 550–557.

Vogel, C. (1994). Management of droughts in South Africa: Past, present and future, *S. Afr. J. Sci.*, **90**, 4–5.

Zerizghy, M. G., Le Roux, P., Hensley, M., and van Rensburg, L. (2013). Prediction of soil distribution on two soil scapes in land type Dc17 east of Bloemfontein, South Africa, *S. Afr. J. Sci.*, **11/12**(109), 1–5.

Zinyengere, N., Crespo, O., and Hachigonta, S. (2013). Crop response to climate change in southern Africa: A comprehensive review, *Global Planet Change*, **111**, 118–126.

This page intentionally left blank

Chapter 5

Crop–Livestock Intensification in the Face of Climate Change: Exploring Opportunities to Reduce Risk and Increase Resilience in Southern Africa by Using an Integrated Multi-modeling Approach

Patricia Masikati[1], Sabine Homann-Kee Tui[1], Katrien Descheemaeker[2], Olivier Crespo[3], Sue Walker[4,5], Christopher J. Lennard[3], Lieven Claessens[6], Arthur C. Gama[7], Sebastiao Famba[8], Andre F. van Rooyen[1], and Roberto O. Valdivia[9]

[1]*International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Bulawayo, Zimbabwe*

[2]*Wageningen University, Wageningen, the Netherlands*

[3]*University of Cape Town, Rondebosch, South Africa*

[4]*Crops For the Future Research Centre, Semenyih, Malaysia*

[5]*University of the Free State, Bloemfontein, South Africa*

[6]*International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Nairobi, Kenya*

[7]*Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi*

[8]*Universidade Eduardo Mondlane, Maputo, Mozambique*

[9]*Oregon State University, Corvallis, OR, USA*

Introduction

The climate of Southern Africa is highly variable at most time-scales and follows a pronounced gradient with arid conditions in the west and humid conditions in the east. There is also a marked latitudinal rainfall distribution pattern, with the southern part having a low rainfall index and high variability and the northern part having higher annual rainfall and lower interannual variability (Kandji *et al.*, 2006). Over the last 100 years, temperatures have increased by about 0.5°C in the region

and downward trends in rainfall have also occurred (Kandji *et al.*, 2006; Morton, 2007). There has also been an increase in drought events with over 15 drought events reported in the region between 1988 and 1992. The frequency and intensity of El Niño episodes have increased. Prior to the 1980s, strong El Niño events occurred every 10–20 years; between 1980 and 2000, the region experienced five episodes with the 1982–1983 and 1997–1998 episodes being the most intense of the century (Reason and Jagadheesha, 2005; Rouault and Richard, 2005). These episodes have contributed to stagnant or decreasing agricultural production and worsening food insecurity in the region (Kandji *et al.*, 2006). Unfavorable climatic conditions and projected climate change are among the major obstacles to achieving food security in the region and also have dire consequences for macro-economic performance.

Climate change impacts

Food insecurity in the region is further exacerbated by low crop production levels that are attributed to inherent low soil fertility and to continuous cropping without addition of adequate organic and inorganic fertilizers due to unavailability and high costs. Feed shortages (especially during the dry season), high incidence of diseases, and high mortality rates cause low livestock production. Undeveloped infrastructure, weak support systems, poorly developed markets, limited understanding of impacts of climate change on agricultural systems, and low investments in climate smart technologies exacerbate the vulnerability of the farming communities. Climate change impacts, when superimposed on the many structural problems in the region where most countries are unprepared or have inadequate adaptation strategies, can easily set-back possible developmental gains by affecting sectors such as agriculture, water resources, and infrastructure (Kandji *et al.*, 2006).

Although countries in Southern Africa are among those that have ratified the United Nations Framework Convention (UNFCCC), expertise in research related to climate change is limited and confined to a few institutions and individuals (Countries' Initial Communications on Climate Change, Malawi (2002), Mozambique (2003), and Zimbabwe (1998)). In the agricultural sector there is limited knowledge on the interactions between projected increases in CO_2, temperature and precipitation variations, and their combined effects on crop and animal production, which hence adds to uncertainties surrounding future smallholder farming systems (Thornton *et al.*, 2009; Countries' Initial Communications on Climate Change, Malawi (2002), Mozambique (2003) and Zimbabwe (1998)). It is imperative for research and development to understand these, as agriculture is the mainstay of the economy in most countries in Southern Africa, employing about 70% to 80% of the population in countries like Zimbabwe, Mozambique and Malawi (Countries' Initial Communications on Climate Change, Malawi (2002), Mozambique (2003) and Zimbabwe (1998)).

Rainfed agricultural production contributes about 35% of the GDP and about 35% to 40% of total export earnings in Southern Africa, excluding South Africa (Naab *et al.*, 2012). The agricultural sector is divided into two broad categories: Large commercial farms and smallholder farming systems. The former intensively use improved technologies and have high production levels, while the latter use limited external inputs and production is very low. The smallholder farmers constitute the majority (about 60% to 70%) of the farmers and are among the poorest and most vulnerable to climate change and variability in the region and the world (Morton 2007; Naab *et al.*, 2012; World Bank Report, 2009). Consequently these farmers face a double risk if adaptation measures are not taken; when there is crop failure there is no food available, and due to their dependency on agriculture for income, they would not have money to buy the food even if it is available on the market (Kandji *et al.*, 2006).

Measures to reduce the impact and risk of climate change in the region have been taken by regional organizations such as the Southern African Development Community (SADC). Since the 1992 drought events, SADC has established a task force under its Food Security, Technical, and Administrative Unit and also proposed a regional drought fund in 2002. At the national level, most countries in the region have established early warning systems that monitor national food supplies and seasonal weather patterns, including seasonal climate outlooks (Kandji *et al.*, 2006).

At the community level, farmers have developed coping strategies to deal with climate variability. Even though these might not be sufficient to deal with increased frequency of droughts, they can serve as useful starting points for interventions by research, government, and development agencies (Morton, 2007). Frequency of extreme events is projected to increase and such events might make timing of agricultural operations difficult and reduce incentives to invest in agricultural production. For example, if crops are damaged at different growth stages (Morton, 2007), replanting might not be a feasible option for smallholder farmers due to financial constraints.

Most studies done in the region have shown that temperatures are likely to increase by $>2^{\circ}$C, and rainfall is likely to decrease (Dimes *et al.*, 2008; Kandji *et al.*, 2006; Morton, 2007; Thornton *et al.*, 2009; Walker and Schulze, 2008) and such changes will affect production of the main staple food, maize, in the medium and long term (Dimes *et al.*, 2008; Morton, 2007; Walker and Schulze, 2008). Although studies have been conducted at varying geographical and temporal scales, they fall short in capturing the complexity and site-specificity of the effects of climate change (Jones and Thornton, 2003). The effects of climate change differ geographically and can be crop-specific: A study in Tanzania showed that although climate change will have negative impacts on maize production, impacts on coffee and cotton, which are cash crops, may be positive (Agrawala *et al.*, 2003 in Morton, 2007). There is also

little work done with regards to the effects of climate change on the biological processes of semi-arid crops and livestock (Thornton *et al.*, 2009; Zimbabwe's Initial Communications on Climate Change, 1998). Studies often elaborate on the communities' vulnerability and adaptation strategies (Jones and Thornton, 2003), but they fail to capture the heterogeneity and diversity within and among the communities and account for livelihood components such as off-farm income and remittances.

Agricultural production systems are complex, with various interacting biophysical (crops, livestock, soil, vegetation, climate) and socio-economic (markets, social institutions, off-farm income and remittances, local customs and policies) subsystems. Consequently, for research and development to have an impact on system efficiency, the potential intervention points need to be identified based on an understanding of the system's individual components and their interactions in space and time. Simulation modeling provides a valuable framework for systems analysis of crop–livestock systems. Component and systems modeling enables analysis of individual components of the complex systems and evaluation of complex interactions and overall systems efficiency.

The current study uses an integrated multi-modeling approach for *ex-ante* impact assessment of climate change and adaptation strategies in heterogeneous smallholder farmers' communities in a particular context. We assess the impact of climate change on crop and livestock production by looking at quantitative production with and without adaptations. We then integrate climate, crop, and livestock projections within the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD; Antle, 2011; Antle and Valdivia, 2011) to assess the economic impacts of climate change and selected adaptation strategies. Here we take into account the heterogeneity of entire farm populations, while understanding that climate change and adaptations will affect households with different resource endowments and thus their ability to invest differently. We also integrate the impacts of projected economic development apart from climate change, by explaining plausible future scenarios. We discuss the costs and benefits of intensification (i.e., increased investments, diversity of activities, as well as economic opportunities) to determine efficient risk reduction strategies and increased resilience in the context of climate change. For our larger study we have considered three countries (Malawi, Mozambique, and Zimbabwe) in Southern Africa (see AgMIP final report); for this chapter, we focus on Zimbabwe.

Farming System Investigated

Settings and locations

The integrated assessment of farming systems was done for Nkayi in northwest Zimbabwe. The district is located between 19°00' south and 28°20' east. Crop production

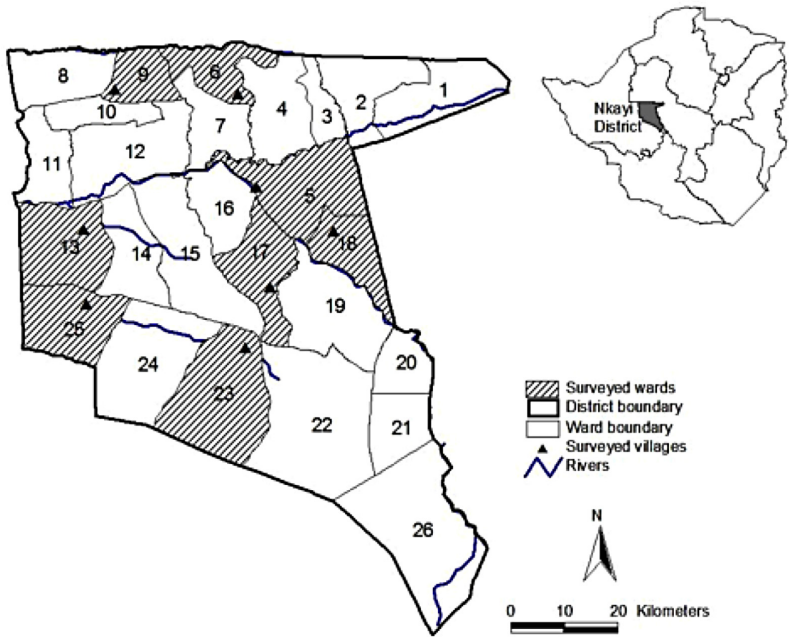


Fig. 1. Study area in Zimbabwe; gray shaded areas are the wards in which household surveys were done.

is rainfed, and average annual rainfall ranges from 450–650 mm. Rainfalls are erratic with a drought frequency of one in every five years (Rockström *et al.*, 2003). Long-term average maximum and minimum temperatures are 26.9°C and 13.4°C, respectively (Fig. 1). The soils vary from inherently infertile deep Kalahari sands, which are mainly nitrogen- and phosphorus-deficient, to clay and clay loams that are also nutrient-deficient due to continuous cropping without soil replenishment. Farmers use mainly a mono-cereal cropping system with addition of low amounts of inorganic and organic soil amendment. Natural pasture provides the basic feed for livestock, and biomass availability is seasonal. During the wet season feed quantity and quality is appreciable, while during the dry season there is low biomass of poor quality. The natural pastures are mainly composed of savannah woodlands, with *Aristida* species, *Eragrostis rigidia*, and *Heteropogon contortus* grass species (Homann *et al.*, 2007).

Crop–livestock farming systems

Mixed crop–livestock production systems are dominant in Zimbabwe (see Fig. 2). These farming systems are mainly based on maize, sorghum, groundnuts, and cowpeas as staple crops, combined with the use of communal range lands, fallow land,

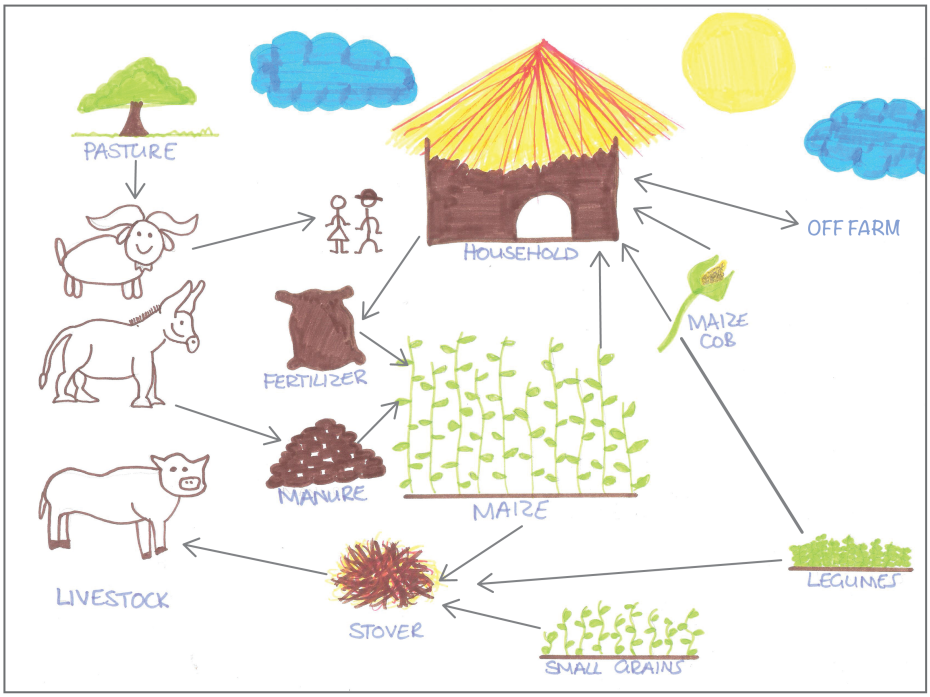


Fig. 2. Schematic representation of the predominant mixed crop–livestock farming systems in Zimbabwe, also found in large parts of Southern Africa.

and crop residues for livestock production. Household livestock holdings vary from a few to a hundred head per household, with varying ratios of cattle (*Bostaurus*), donkeys (*Equusasinus*), and goats (*Capra hircus*) (Bossio, 2009; Williams *et al.*, 2002). Livestock play an important role in these farming systems as they offer opportunities for risk spreading, farm diversification, and intensification, and provide significant livelihood benefits (Bossio, 2009; Williams *et al.*, 2002). Animals are kept to complement cropping activities through the provision of manure for soil fertility maintenance, draft power for cultivation, transport, cash, and food, while crop residues are used as adjuncts to dry-season feed (Masikati *et al.*, 2013; Peden *et al.*, 2009; Powell *et al.*, 2004; Williams *et al.*, 2002).

These systems evolve in response to various interrelated drivers, such as increased demographic pressure along with higher incomes earned by the urban populations, which results in a growing demand for crop and livestock products with the development of local and urban markets (Table 1; Homann-KeeTui *et al.*, 2013). This increased demand for crop and livestock products could benefit small-scale farmers as they gain access to markets, if they are able to intensify and diversify production in a sustainable way. This would reduce risk and increase resilience by

Table 1. National- and local-scale drivers that influence current farming systems in Nkayi, Zimbabwe.

National-scale drivers	
GDP *per capita* (average USD, 2003–2009)	422.3
Annual GDP growth (av. %, 2003–2009)	−6.4
Livestock (% agric. gross production, 2009)	44.8
Public spend on agriculture (av. %, 2003–2009)	8.6
Rural population (%, 2009)	62.2
Net imports (Mio USD, 2008)	
Maize	169.8
Milk	2.2
Local-scale drivers	
Rainfall (mm annual average)	650
Human density (2008, per km^2)	21
Main crops	Maize, small grains, legumes
Main livestock	Cattle, goats
Soil fertility and land management	Cattle, goats
Extension support	Fair
Market development	Fair

Source: Homann-Kee Tui *et al.* (2013).

providing farmers with diverse sources of income. Given that currently productive resources in these systems (although limited) are being used inefficiently, as evidenced by low production, a shift towards resilient and more productive systems is the key to future food security. Low production in smallholder farming systems is due to a combination of factors that include unfavorable climatic conditions, poor and depleted soils, environmental degradation, and low level of capital endowment that leads to limited uptake of improved technologies, in conjunction with failed sectorial and micro-economic policies (Kandji *et al.*, 2006; Morton, 2007; World Bank Report, 2009). Climate variability and change stressors, superimposed on the many structural problems in smallholders farming systems where there is not much support nor adequate adaptation strategies, can exacerbate food insecurity and increase vulnerability (Kandji *et al.*, 2006; Morton, 2007).

Stakeholder Interactions, Meetings, and Representative Agricultural Pathways

Stakeholder interactions and meetings

In this study, we engaged stakeholders in a process to design a set of plausible representative agricultural pathways (RAPs) for future economic development at the

project site. The RAPs provide the parameters for the long-term projections of economic development. They are also a source of reference for predictions that affect smallholder farmers with limited market connections, in comparison with global model projections (e.g., IMPACT, SSP2_HGEM_DSSAT_5crop scenario, AGMIP reference scenarios). The stakeholder consultations were conducted as structured expert discussions at provincial level with six knowledgeable representatives from National Agricultural Research and Extension Systems (NARES), including government departments of crop and livestock production and agricultural economics. The discussions lasted about three to four hours. Separate talks were held with private sector representatives, including agrodealers and meat processors.

At the meeting with experts, the RAP concept was introduced, using the CCAFS national scenario (Ingram and Ainslie, 2011) as a visual aid to create a clear vision for the country, and to identify possible development scenarios and implications. To create an informed, engaged, and critical discussion and common understanding of the current situation, background material was shared and participants exchanged information on perceived poverty trends, major economic drivers for national and regional development, the role of agriculture, and major challenges and opportunities for agricultural development. A given list of indicators was extended, which included indicators that participants found relevant for the study case. Participants then agreed on a possible pathway; one that acknowledges the challenging economic conditions Zimbabwe is facing, but with positive assumptions for economic development. Participants used background information, their expertise, and their intuition to jointly define the RAP, including a catchy title, key indicators, magnitude of the changes, and rationale. Documentation of the narrative and the indicators was shared with the participants, experts, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) research team, and outside economists for review.

Representative agricultural pathways (*RAPs*)

Involvement of stakeholders by using a participatory approach is very important in assessing the climatic and non-climatic stressors on agricultural production systems. Stakeholder participation enhances collective knowledge and shared visions on how to manage natural resources to benefit communities effectively and to develop interventions aimed at improving farming systems. Interventions developed by using participatory approaches have a better chance of being accepted, appropriately planned, and maintained because they originate from a process that involves engagement rather than being a top–down process in which solutions are imposed from outside (e.g., without consultation or interaction). Dorward *et al.* (2003) found that low adoption could be attributed to lack of stakeholder participation in developing the

technologies, and lack of consideration of market accessibility and incentives. In dealing with changing complex systems, natural resource management initiatives are increasingly turning towards participatory modeling procedures to integrate local, expert, and specialized stakeholder sources of knowledge effectively (Carberry *et al*., 2003, Jones *et al.*, 2008; Masikati *et al*., 2013).

Data and Methods of Study

The AgMIP integrated assessment approach was used to understand how crop and livestock productivity and net returns of the various farming activities would change under the different adaptation strategies in the current climate as compared to the mid-century climate scenario (2040–2070; Antle and Valdivia, 2013). This was done using climate, crop, livestock, and socio-economic models. To assess the sensitivity of the current farming systems to climate change we used climate data for mid-century (2040–2069) obtained from 20 GCMs under RCP8.5. For the full integrated assessment of the impacts and benefits of climate change on future agricultural production systems with adaptations and RAPs, we used mid-century climate data from five GCMs (E, I, K O, R). We assessed the impacts of climate change on maize production without adaptation strategies by using 20 GCMs, while the full integrated assessment was done with adaptation strategies by using five GCMs. For more information, see Table 2.

Table 2. Treatments and adaptation strategies used to assess the impacts and benefits of climate change on current and future crop production systems in Nkayi, Zimbabwe.

Treatments Used in Assessing the Sensitivity of Maize Production to Climate Change in Zimbabwe	
Production	Treatment
Crops	Maize production under farmer practice (low-input system), average fertilizer application: 3 kg/ha* and average manure application: 300 kg/ha*.
Adaptation Strategies Used for Integrated Assessment of the Impacts and Benefits of Climate Change on Future Agricultural Production Systems with Adaptations and RAPs	
District	Treatment
Nkayi	Maize production under micro-dose (17 kg N/ha). Maize under the recommended fertilizer application rate 52 kg N/ha. Maize under maize–mucuna rotation at 30% residues retention.

*ICRISAT Survey 2008. Crop residues obtained from the above crop production systems were fed to livestock as adjuncts to dry season feed.

Climate

Observed trends in temperature and precipitation

The climate of Southern Africa is highly seasonal with hot, wet summers and cool, dry winters. This is largely a function of the movement of the Intertropical Convergence Zone (ITCZ) and a semi-permanent high-pressure band located over the subtropical extent of the region that results from the descending limb of the Hadley circulation. During summer, the ITCZ is situated south of the equator and the high-pressure band to the south of South Africa. Summer rainfall is typically convective and may be linked to large-scale synoptic features like mesoscale convective systems, tropical temperate troughs, and thermal lows in the subtropics, which may form a close low pressure. Tropical cyclones may also impact Mozambique in the late summer. During winter, the northward movement of the ITCZ is accompanied by a northward movement of the high-pressure band over the region, which has subsiding air that causes dry, colder winters in the region.

1980–2010 baseline climate data construction

According to AgMIP climate data protocols, a baseline daily weather dataset (1980–2010) was produced based on the best available daily datasets with regard to geographical proximity, data length, and quality. Daily minimum and maximum temperatures, as well as rainfall, were used. For our study site, historical daily records were made available from Department of Meteorology, Zimbabwe and had nearly 50% missing data for temperatures and rainfall over 31 years at Nkayi station (19.00°S, 28.90°E).

Crop models require complete daily datasets as inputs. However, most climate datasets obtained from the meteorological departments in most countries in Southern Africa would be incomplete with regard to crop modeling requirements. The finished climate dataset for Nkayi consisted of observed and filled data (from AgMERRA, Ruane *et al.*, 2014) to form the station's baseline climate. Solar radiation (for APSIM; Agricultural Production Systems Simulator) and potential evapotranspiration (for DSSAT; Decision Support System for Agrotechnology Transfer) were not available in the station data and these were estimated on a daily time-scale by using temperature and rainfall from the baseline, latitude, and altitude. Each 31-year dataset was formatted according to AgMIP protocols to ensure data uniformity. To satisfy the point-based nature of the crop models as closely as possible, the baseline datasets were climate-corrected to create virtual climate stations at the location of each of the studied farms. The correction factors were extracted from the WorldClim monthly mean temperature and monthly total rainfall.

Maximum and minimum temperatures and rainfall were analyzed for historical averages, variability, and trends (Fig. 3 and Table 3). The station shows weak positive

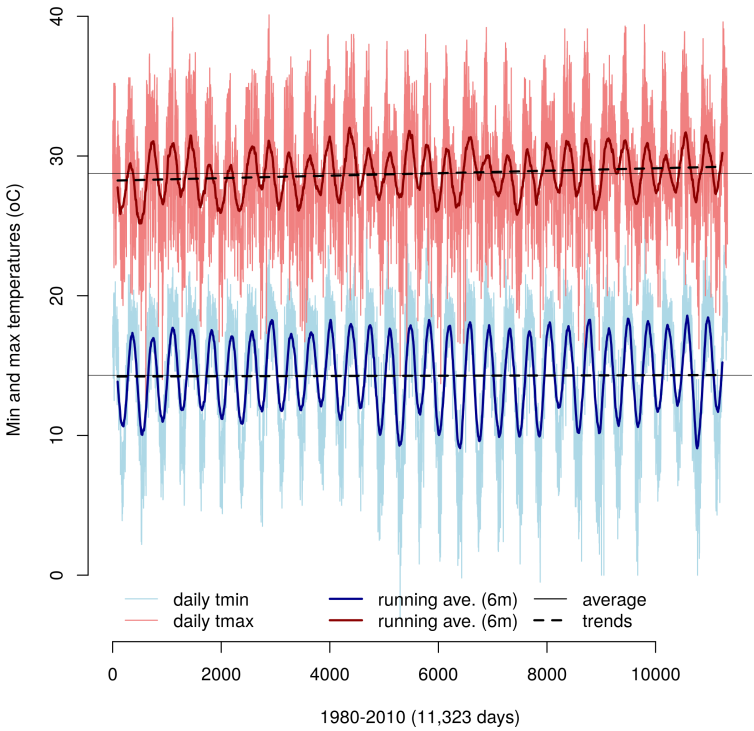


Fig. 3. Minimum and maximum temperature baseline trends for Nkayi, Zimbabwe (ZWNK). Maximum temperatures show an increasing trend over 1980–2010 (approx. 0.3°C per decade).

Table 3. Historical climate and annual trends of the Nkayi station.

Variable	Average	Highest	Lowest	Trend (°C or mm/year)
T_{min} (°C)	14.6	26.0	−2.9	0.0034
T_{max} (°C)	29.0	40.5	12.5	0.032
Rainfall (mm/day)	1.65	81.8	0	—

trends in both minimum and maximum temperature; however, these trends are not statistically significant.

Significance tests for delta method changes

The AgMIP global climate team uses a significance threshold of change. Based on the Z-test of significance, lower and upper significance thresholds are computed at each station, which rely on the 31-year baseline period. This bandwidth is used to categorize separately future temperature and rainfall projections that remain within

expected statistical deviation, in opposition to those changing beyond the expected deviation, which hence suggests a climate change beyond natural variability.

The significant change amplitude is computed as 0.36 of the standard deviation of the monthly (growing season only) averages over the 31 years. This amplitude subtracted and added to the average gives respectively the lower and upper limits of significant change and plotted as dashed horizontal (rainfall) and vertical (temperature) dashed lines in Fig. 5.

Climate projections

Future projections of rainfall and temperature from 20 general circulation models (GCMs) were made under the RCP8.5 scenario for the period 2040–2070. The creation of the future climate datasets consisted of perturbing the baseline by following a delta approach. This study relies on daily future datasets that result from a monthly shift of daily mean temperatures and a monthly proportional variation of daily rainfall events. In each case, boundary conditions (e.g., large amplification of an extremely high-rain event) were tested and dealt with according to AgMIP standards (Rosenzweig *et al*., 2014). The deltas were computed at the GCM grid-box scale, for each individual GCM, for each individual RCP, from the 30-year long baseline (1980–2009) to the 30-year-long future period. Each future scenarios is formatted as a standard *.AgMIP format, which can be translated automatically into the desired crop model format through the QuADUIAgMIP tool (Rosenzweig *et al*., 2014).

Rainfall is projected to decrease over most of Southern Africa, particularly over the west and central regions, except over east South Africa and Mozambique where the change is uncertain (Fig. 4). Temperature is projected to increase across the whole region. Changes range from large increases inland (above 3°C in southwest Botswana and surrounding areas) to smaller increases in coastal areas. For our study site, the projections indicate a 5% to 10% decrease in rainfall and temperature increases of at least 3°C for the period 2040–2070.

It is important to understand climate future projections during the crop growing season since more than 90% of agriculture production is rainfed. For the Nkayi station for the months of October to March, the 20 GCMs show that temperatures are likely to increase (Fig. 5). Rainfall projections show both decreases and increases, which is partly due to the high complexity of rainfall simulation, and suggest less-clear future directions. Projected temperature increase is on average between 2–3°C, an increase that is projected across all months. There is no clear projected rainfall change except in the months of October and November where the majority of the GCMs project a slight decrease rainfall. There is much better agreement between GCMs in the temperature projections than in rainfall, as all

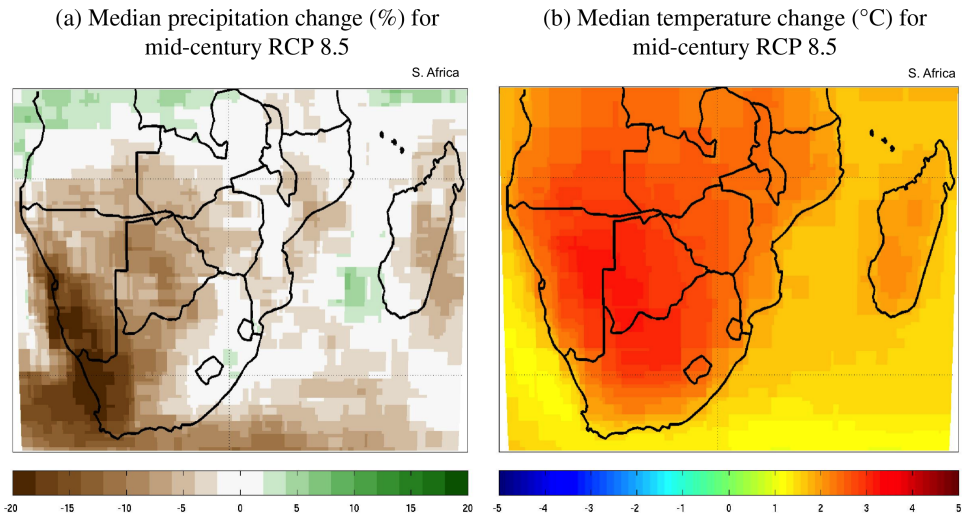


Fig. 4. Median precipitation (%) and temperature (°C) changes for mid-century (2040–2070) under RCP8.5 for Southern Africa.

the climate model projections lie outside the natural variability envelope during the rainy season for temperature. Nkayi is therefore projected to become warmer during the growing season with a possible reduction in early-season rainfall.

Crops

Crop model calibration (DSSAT and APSIM)

The predictive performance of the APSIM and DSSAT crop models was evaluated using on-farm experimental data obtained from ICRISAT research work under different projects in Nkayi (Homann-KeeTui *et al.*, 2013; Masikati, 2011). Both models were calibrated for maize and APSIM was also calibrated for the forage legume, mucuna (*mucuna pruriens*; Tables 4 and 5). Results were satisfactory (Figs. 6a–d) with an observed mean maize grain yield of 1115 kg/ha and simulated yields of 1185 and 1234 kg/ha for APSIM and DSSAT models, respectively. The root-mean-square error (RMSE) was 283 and 480 for APSIM and DSSAT. However, the models had a tendency to over-predict maize biomass (Figs. 6c, d) with a mean observed biomass of 2460 kg/ha and mean simulated biomass of 3385 and 3874 kg/ha for APSIM and DSSAT, respectively. For mucuna biomass (Fig. 6e) results were satisfactory with mean observed yields of 4263 kg/ha and a simulated yield of 4224 kg/ha with an RMSE of 165.

Both models (APSIM and DSSAT) were also evaluated for their ability to simulate maize grain yield variability across farming households (Fig. 6f). The models

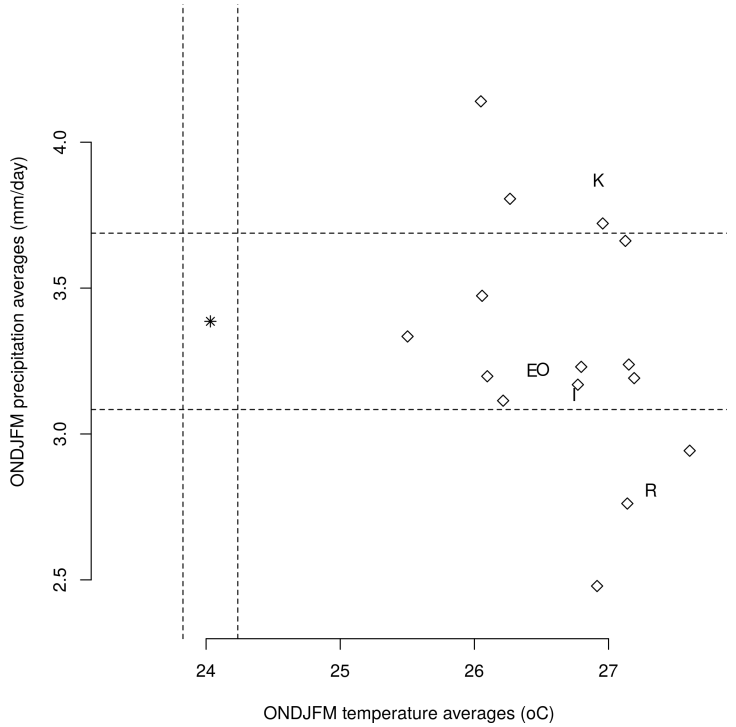


Fig. 5. Mid-century temperature and precipitation changes at Nkayi, Zimbabwe from 20 GCMs under RCP8.5. Dashed lines indicate the bounds of historical natural variability of rainfall. The * represents current baseline climate (1980–2010). GCMs represented by letters are used for full integrated assessment on impacts and benefits of climate change on farming systems with adaptations and RAPs.

Table 4. Genetic coefficients.

Crop	Maize		
Variety	SC 401		Mucuna
Crop models	DSSAT	APSIM	APSIM
Thermal time from emergence to end of juvenile stage (degree days)	230	230	Mucuna, long maturing variety and harvested at flowering stage.
Thermal time from silking to physiological maturity (degree days)	730	730	
Maximum possible number of kernels per plant	500	500	
Kernel filling rate (mg/day)	8	8	

Table 5. Soil initial conditions used for calibration of APSIM and DSSAT crop models. Soil samples were collected from experimental sites in December 2008 from Nkayi, Zimbabwe.

	Soil layer (cm)					
Parameter	0–15	15–30	30–45	45–60	60–75	75–100
Organic carbon (%)	0.52	0.43	0.35	0.30	0.21	0.21
*NO_3–N (ppm)	3.08	2.16	2.30	2.21	2.55	1.07
Air dry (mm/mm)	0.03	0.07	0.09	0.09	0.09	0.09
*LL 15 (mm/mm)	0.06	0.10	0.13	0.13	0.18	0.22
*DUL (mm/mm)	0.16	0.18	0.19	0.20	0.22	0.24
*SAT (mm/mm)	0.41	0.41	0.41	0.37	0.36	0.34
Bulk density (g/cm^3)	1.43	1.42	1.42	1.55	1.55	1.61

Source: Masikati (2011).
*NO_3-N = Nitrate–nitrogen, LL 15 = crop lower limit, DUL = drained upper limit, SAT = saturation

showed the capacity to simulate the middle yield range from the farming households but did not perform so well for the lower and higher ends, especially the DSSAT model. To offset the models' effects on projected future yields, the simulated yields were bias-corrected before doing the economic analyses; the biomass yields were also adjusted before they were fed to livestock.

After evaluation, the models were used to assess the impact of climate change on maize production with and without adaptations and the RAPs. Mucuna was evaluated as it was used as an adaptation strategy for the crop–livestock systems in Zimbabwe. However, only the APSIM model was used to assess the effects of mucuna on maize and livestock production, as routines required to harvest mucuna at the flowering stage are currently not available in the DSSAT model. The full integrated assessment included adaptation strategies, namely micro-dose application of fertilizer at 17 kg N/ha on total maize area, recommended rate of fertilizer application at 52 kg N/ha on the total maize area, and a mucuna strategy. The latter strategy consists of growing mucuna on one third of the maize area; the other third of the field would have maize that has 30% of total harvested mucuna residues in the soil, and feeding the remainder to cattle by using the LIVSIM model, while the final third would have maize under micro-dose treatment. It is important to note that the approach used for this study was mainly to assess the impact of year to climate variations on crop production, hence the residual effects of mucuna on subsequent maize were not taken into account in maize yield. The C:N ratio for mucuna used was 14 and the biomass was applied annually before planting (Capo-chichi, 2002).

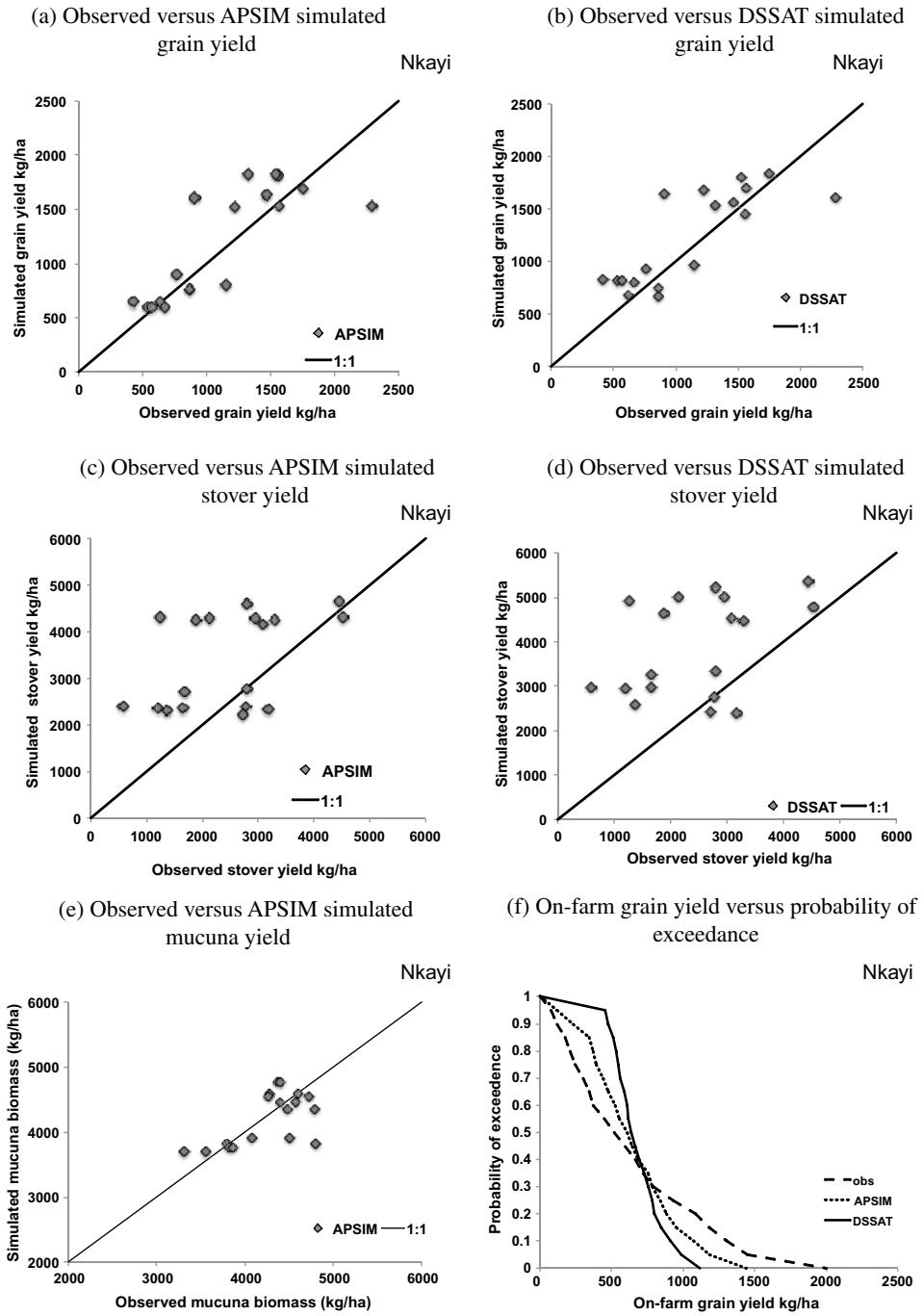


Fig. 6. APSIM and DSSAT crop model calibration by using (a–e) on-farm experimental data from Nkayi, Zimbabwe and (f) survey data, which show the distribution of observed and simulated maize grain yields across different farms.

Livestock

Household-level livestock production was modeled with LIVSIM (LIVestockSIMulator, Rufino *et al*., 2009). LIVSIM simulates production with a monthly time step, based on breed-specific genetic potential and feed intake, by following the concepts of Konandreas and Anderson (1982), and by taking into account specific rules for herd management. Energy and protein requirements are calculated based on AFRC (1993), whereas actual feed intake is simulated according to Conrad (1966). The simulated livestock production outputs used in this chapter included milk production and herd dynamics, such as animal sales, calving, and mortality rates.

The impact of climate change and the various adaptation strategies on livestock production was predicted based solely on simulated changes in on-farm feed production that resulted from the crop model runs. Livestock rely on community range-lands throughout the whole year and, in the dry season, crop residues constitute an important feed base component that help farmers to keep their animals alive and in reasonable condition (Fig. 7a; Masikati, 2011). However, the feed quality of the crop residues and of the dried grasses in the rangeland is low and the risk

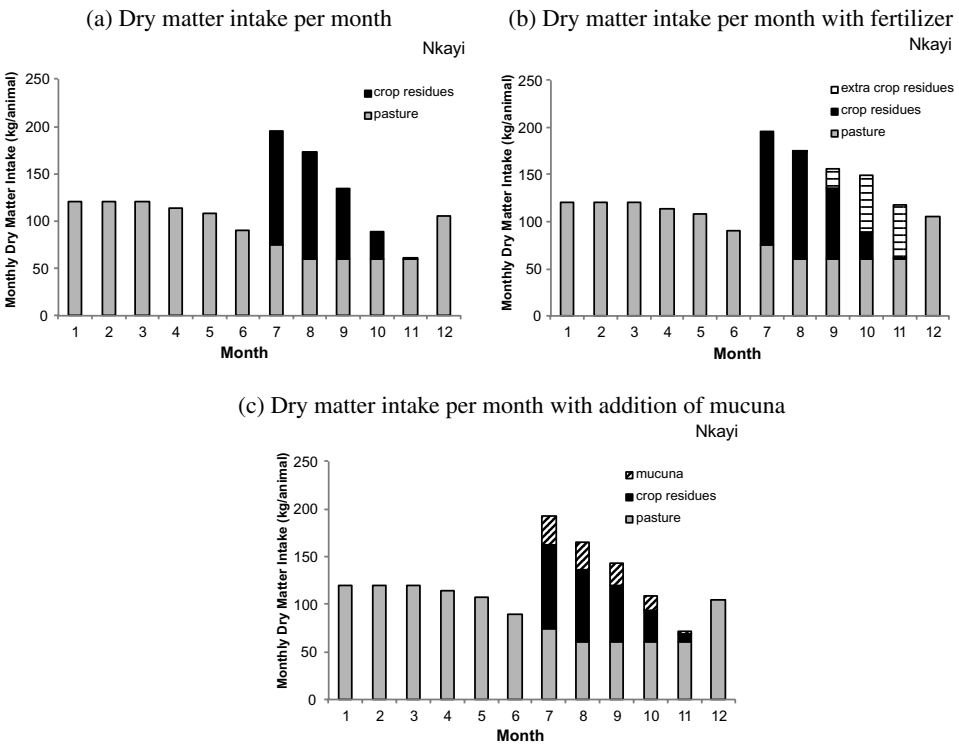


Fig. 7. Feedbase for cattle in Nkayi, Zimbabwe (a) in the baseline scenario, (b) with recommended fertilizer application to maize, and (c) with inclusion of mucuna on one third of the maize land.

of low crop production during dry years is relatively high. Therefore, feed gaps in the dry season are common, which leads to important inefficiencies in the livestock component of the system. On-farm feed production and composition change and the effects of these changes on livestock were simulated with LIVSIM for climate change and due to the various adaptation strategies. The effects of increased crop residue availability in the fertilizer adaptation strategies and of higher-quality feed in the mucuna strategy (Figs. 7 b, c), were investigated. Potential changes in rangeland productivity and direct effects of temperature on animal performance were not taken into account in this study.

Livestock model calibration (*LIVSIM*)

The LIVSIM model was earlier calibrated for Zimbabwean conditions and the Mashona breed, for which it is also used here (Rufino, 2008; Rufino *et al.*, 2011). Comparison of the simulated livestock outputs with the data collected from the households in the survey shows that the model predictions overestimated reported milk yields by, on average, 560 l per year. This difference can be accounted for by the milk consumption by calves, which is included in the model output and not in the values given by farmers.

Comparison of simulated with observed data on herd dynamics is more difficult than for milk. In reality, herd dynamics are influenced by factors that are not modeled, such as diseases and farmer decisions on, for example, selling, which may be influenced by sudden cash needs. However, simulated mortality and calving rates should at least correspond with the average observations across the households in a community. The average simulated mortality rate of 0.11 (across 30 years and 92 households) was within the range of the observed average and median values of 0.20 and 0.03, respectively, across the 92 households. The average simulated calving rate of 0.26 was similar to the observed 0.20.

The simulated average annual milk production varies greatly between households from 365 l to 2581 l, with an average of 1010 l per year under current climate and zero fertilizer (Fig. 8). These differences are largely explained by differences in herd size, ranging from 1–61 heads of cattle. Herd dynamics, including mortality and calving rates, are related to feed availability, which affects the animals' performance and health, and depends on the number of animals per cultivated area.

Economics

Survey data

The TOA-MD model (Antle and Valdivia, 2014) was used to simulate the economic tradeoffs between current and future climate and the selected adaptation strategies,

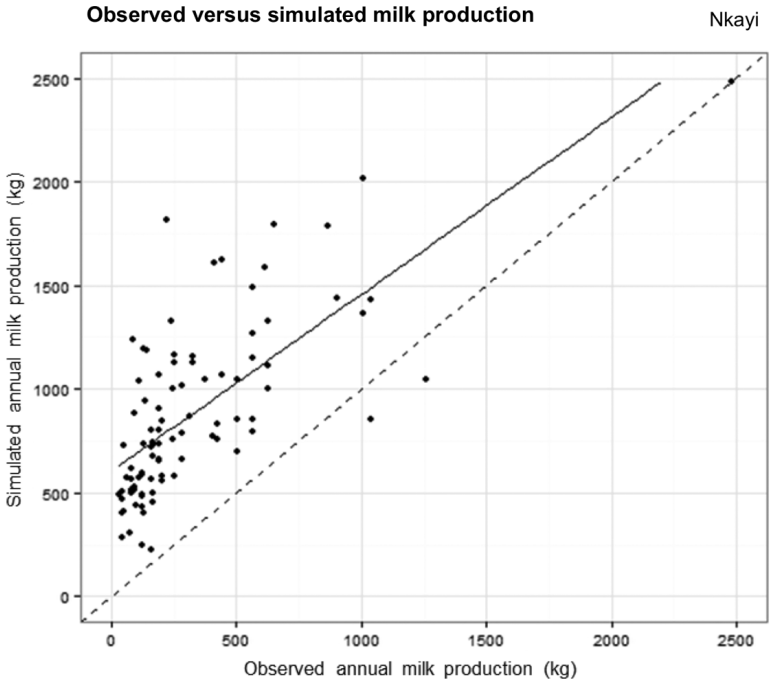


Fig. 8. Scatterplot of simulated vs. observed annual milk production for the households with cattle in Nkayi, Zimbabwe ($n = 92$).

as well as the associated economic outcomes for specific farming systems and their heterogeneous farm populations.

The model draws on various data sources:

- Household survey data: Household surveys conducted in 2011 with 160 farmers interviewed in eight villages assessed farm and household size, off-farm income, revenues from crops and livestock, and the costs of production. Complementarily, eight focus group discussions, one per each village surveyed, assessed agricultural output and input prices, perceived as normal prices during the observation year, not peak prices (Homann-KeeTui *et al.*, 2013).
- Biophysical model inputs: Crop and livestock simulations projected crop yields and livestock performance for the climate change and adaptation scenarios. They were matched with the crop and livestock outputs generated through the household survey through a bias-correction.
- RAPs: Stakeholder consultations were used to estimate exogenous growth rates and price trends for the future mid-term (2050s) scenarios.

For the assessment of net returns we estimated the monetary values of the multiple crop (grain and residues) and livestock (sale, draft power, manure, milk) outputs and

valued the outputs used, consumed, or sold at opportunity costs, whereby internally used crop and livestock outputs were factored in as costs under the respective activities, by taking into account the local-user practices (Table 6). We modeled climate change and adaptation strategies for maize and cattle activities and used the RAP assumptions to account for the changes in other crops and other livestock activities, which included higher product prices, input uses, and input prices. We incorporated further relevant changes to the systems following the RAP assessments: Reduction of the farm-household cultivated land, increases in family and herd sizes, and less off-farm income.

Households were stratified into three categories based on cattle herd size, as this influences farmers' wealth status and their ability to invest in alternative technologies (Table 7).

RAPS narrative and development

We based the economic analysis on a representative agricultural pathway and scenario (RAPS) with the optimistic assumption that Zimbabwe will move out of the economic crisis towards positive economic development. By acknowledging the challenges and time required for institutional change, proactive governance and investments, we assume conservative projections. The goal of the RAPS is to unlock the potential for growth through integrated market-oriented crop and livestock production. Zimbabwe is stepping out of 15 years of economic crisis. The government seeks to promote market-oriented agricultural production and restore investor confidence. Severe liquidity constraints, however, restrict public and private investments. Local markets are not well integrated into international markets. Limited employment opportunities in urban areas reduce rural–urban migration. Climate change contributes to low and fluctuating crop yields. Tables 8 and 9 summarize the projected socio-economic changes, projected prices, and external growth rates for agricultural outputs and the narratives, which were based on the RAPS and used for the TOA-MD simulations.

Under these conditions, we assume 140% exogenous yield growth for maize as the predominant crop, and 135% growth for small grains and legumes (Table 9). Fodder crops were only recently introduced and no market exists; we therefore do not expect growth.

We assume 130% exogenous growth for cattle and 125% for small stock offtake, essentially by reducing mortality and improving livestock quality, and 10% increased milk, manure, and draft power production.

Low production and poor-quality produce contribute to a slow-down in producer price increases. Product price increases at international markets are not much transmitted to the local level. We assume price growth for maize grain and residues to

Table 6. Variables, reference prices and assumptions for the definition of crop and livestock revenues and variable costs, under farmer practice, fertilizer treatments, and maize mucuna rotation.

Variables	Units	Reference prices	Assumptions
			Crops
Revenues			
Maize grain	US$/kg	0.2	Village-market price for maize sales.
Other grain crops	US$/kg	0.25	Village-market price for small grain and legume sales. Higher prices as compared to maize were explained by higher labor cost.
Maize residues	US$/kg	0.04	Farmer-estimated price of crop residues, highest prices for legume residues. Crop residues are not sold. This price might reflect the labor for collecting the residues.
Other residues	US$/kg	0.02–0.08	
Mucuna residues	US$/kg	0.13	75% of equivalent feed value of mucuna biomass.
— Feed equivalent	US$/kg	0.13	75% of equivalent fertilizer value of mucuna biomass.
— Mulch equivalent			
Costs			
Estimated costs for external inputs	US$/year	Lump sum	Farmers individually estimated their total costs for external inputs in crop production during the observed year.
Draft power	US$/ha	20	Village price for animal draft power. Applied to the land cultivated by draft power.
Manure	US$/kg	0.04	Farmers estimated price of manure. Applied to the rates of manure use.
Mulch	US$/kg	0.04	Farmers estimated price of maize residues
— Maize residues	US$/kg	0.13	for soil amendment.
— Mucuna residues			Equivalent fertilizer value of mucuna biomass as soil amendment.
Fertilizer non-subsidized	US$/kg	0.7	Village market price, assuming availability of fertilizer.
			Livestock
Revenues			
Draft power	US$/draft animal/day	3.3	Derived from local price for animal draft power (20US$/ha), and considering that a pair of oxen ploughs about 0.3 ha/day.

(*Continued*)

Table 6. (*Continued*)

Variables	Units	Reference prices	Assumptions
Milk	US$/l	1	Village-market price for milk.
Manure	US$/kg	0.04	Farmers estimated price of manure. This price might reflect the labor for collecting the manure.
Herd flows — Cattle	US$/kg live weight	1.3	Village-market price that reflects the average quality of cattle at markets in the communal farming sector.
— Other livestock	US$/kg live weight	1	Village-market price that reflects the average quality of goats at markets in the communal farming sector.
Costs			
Estimated costs for external inputs	US$/year	Lump sum	Farmers individually estimated their total costs for external inputs in livestock production during the observed year.
Feed — Crop residues — Mucuna residues	US$/kg US$/kg	0.04 0.13	Farmers' estimated price of crop residues. Equivalent feed value of mucuna biomass.

be 110% and 103%, respectively, and for other crops grain and residues to be 110%. For cattle and small stock in the future we assume 15% and 10% price increase for live animal sales and 5% increase for the other products that are usually not traded. The influx of cheap imports also contributes to slow producer price growth. Input prices tend to remain high and inputs are not affordable for most smallholder farmers. Input support is limited to vulnerable households during recovery and rehabilitation. In these elements of the farming system that were not simulated by the crop and livestock models, future changes were estimated both with and without climate change.

Adaptation package

The adaptation package was purposely designed for resource-limited households under low and erratic rainfall conditions, with emphasis on low costs, which implies low risk, and by making use of locally available resources. We therefore first tested the effects of different fertilizer application rates (17kg N/ha, micro-dosing, and 52 kg N/ha, recommended rate) on subsequent maize, as well as organic fertilizer in a maize mucuna rotation.

Table 7. Base-system characteristics of 160 mixed farms used for the analysis, by farm type, in Nkayi, Zimbabwe.

Variables	Units	0 Cattle Mean	1–8 Cattle Mean	>8 Cattle Mean	Total Mean	Total Std. Dev.
Proportion in community	%	42.5	38.1	19.4		
Household members	People	5.9	6.9	7.4	6.6	2.5
Proportion of female-headed households	%	27.9	31.1	22.6	28.1	
Net returns (maize)	US$/farm	60	162	63	100	121
Net returns (other crops)	US$/farm	31	62	35	44	53
Net returns (cattle)	US$/farm	0	472	1347	443	586
Net returns (other livestock)	US$/farm	9	19	15	14	29
Off-farm income	US$/farm	220	300	294	265	217
Farms with maize	%	98.5	100.0	100.0	100.0	0.1
Maize area	Ha	1.1	1.4	1.8	1.3	0.8
Maize grain yield	kg/ha	497	826	675	657	531
Farms with small grains	%	23.5	32.8	41.9	30.6	46.2
Small grain area	Ha	0.7	0.7	1.0	0.8	0.8
Small grain yield	kg/ha	393	726	327	512	622
Farms with legumes	%	33.8	49.2	48.4	42.5	49.6
Legume area	ha	0.4	0.4	0.5	0.4	0.3
Legume yields	kg/ha	452	722	388	557	541
Cattle*	TLU	0	5.4	13.9	4.7	4.7
Other livestock*	TLU	0.3	0.5	1.6	0.6	0.9

*Herd size: cattle = 1.14 tropical livestock unit (TLU), donkeys = 0. 5 TLU, goats and sheep = 0.11 TLU.

The package that was finally applied across all types of households included the following components:

- Adoption of long duration maize varieties instead of short duration varieties, with grain yield increases between 8% and 18%, and residue increases between 5% and 11%.
- Converting one third of the maize land to maize–mucuna rotation, 30% of the mucuna biomass left on the fields as inorganic fertilizer for subsequent maize. 70% fed to cattle or available for sale.
- Application of micro-dosing (17kg N/ha) on one third of the maize field, second year after the maize mucuna rotation.

Table 8. Changes in socio-economic parameters, 2005–2050, based on the RAPS.

Parameter	Direction of change	Percentage change	Narrative
Family size	++	105	Restricted alternatives in urban areas reduce the rural–urban migration and result in more labor available in rural areas.
Farm size	− −	120	By using improved and labor-saving technologies, farm households will intensify production towards greater production on less land.
Herd size	++	115	Few farms will keep fewer animals in better conditions, the majority will diversify and this will lead to overall increases in livestock numbers
Off-farm income	–	110	Off-farm income has been playing an important role, the opportunities seem however increasingly restricted.

Note: ++ = medium increase, − − = medium decrease, – = small decrease.

Core Question 1: What Is the Sensitivity of Current Agricultural Production Systems to Climate Change?

Impact of climate change on crop production

Maize production in Nkayi, Zimbabwe

The APSIM and DSSAT crop models were used to simulate the effects of climate change on maize grain and stover production under the current farmers' practice (average fertilizer application of 3 kg N/ha). Both models predicted average yield reductions under most GCMs (Fig. 9a). Average simulated maize grain and stover yield reductions were –7% and –9% for APSIM, respectively, while for DSSAT they were –6% and –1%. Predicted yield reductions are not very pronounced under the current farmer practice as it is already a low-productivity system (due to depleted soils). The two crop models also agree on the shortening of days to flowering and maturity across the different GCMs. The APSIM model predicted a shortening of days to flowering and maturity of 11% and 12%, while DSSAT predicted 10% and 11%, respectively; the length of the maize growing period is projected to be shorter due to projected temperature increases which favors rapid crop development. Maize grain and stover yield reductions could mainly be attributed to increased temperatures coupled with reduced rainfall. See, for example climatic conditions under GCM R (Fig. 5) or GCM 18 (Fig. 9a).

Table 9. Current and projected producer prices and exogenous growth rates for agricultural outputs 2005–2050, without and with climate change, based on the RAPS.

		Without climate change		With climate change		
Outputs	Units	Projected price growth (%)	Projected exogenous growth (%)	Projected price growth (%)	Projected exogenous growth (%)	Narrative
Maize						
Grain	USD/kg	110	140	120	140	Village-market price for grain; residues are not traded. Most households have a food grain deficit; surplus for sale is limited. Maize remains the staple crop; intensification has large potential to contribute to growth, but depends on substantial investment.
Residues	USD/kg	103	140	105	140	
Other crops						
Small grains	USD/kg	110	130	115	130	Price increases of other crops are below maize. Groundnut prices can increase more than small grains. Growth potential is higher than for maize, and the contribution will increase.
Residues	USD/kg	103	130	105	130	
Legumes	USD/kg	110	130	115	130	
Residues	USD/kg	103	130	105	130	
Cattle						
Sales	USD/kg live weight	110	130	120	130	Live animals are being sold; milk; mainly for consumption; draft power and manure are in-kind exchanges. Investment in feed and improved management has great potential to reduce mortality, increase productivity and quality; little confidence however in producer price increases.
Milk	USD/l	103	110	105	110	
Draft	USD/draft animal/ day	103	110	105	110	
Manure	USD/kg	103	110	105	110	
Other Livestock						
Sales	USD/kg live weight	110	120	110	120	New attention to other livestock will lead to productivity growth.
Milk	USD/l	105	110	105	110	
Manure	USD/kg	105	110	105	110	

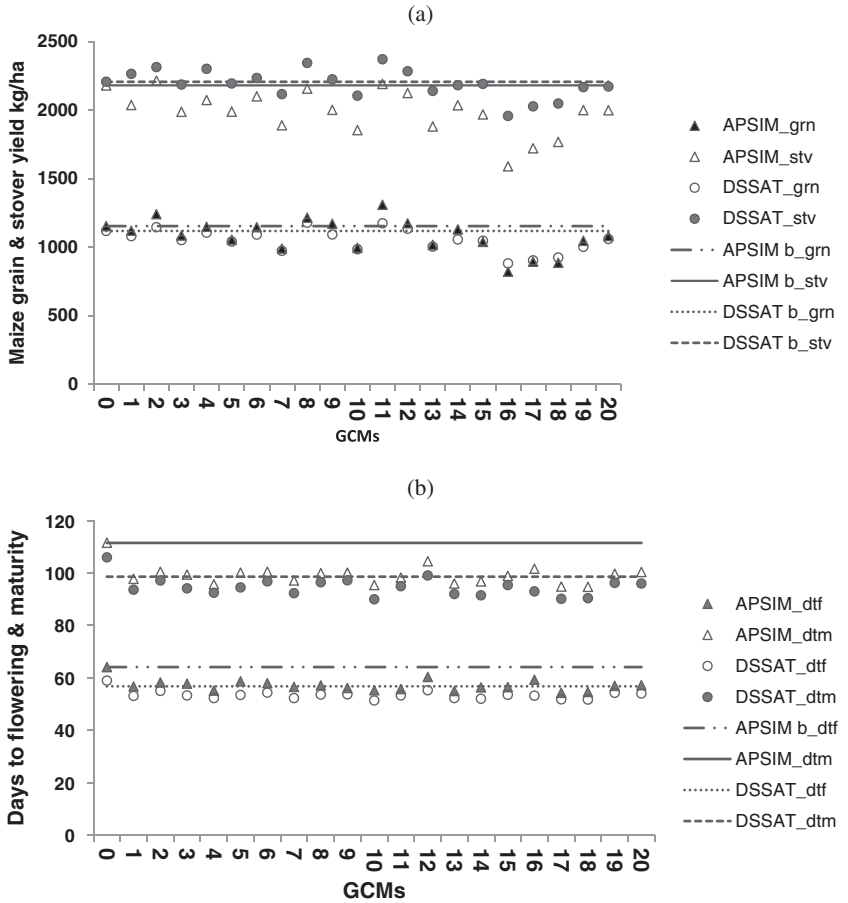


Fig. 9. Sensitivity of maize production to climate change in Nkayi, Zimbabwe. Twenty GCMs were used (A–K denoted by numbers 1–20; 0 denotes the baseline climate 1980–2010). RCP8.5 mid-century (2040–2070).

Impact of climate change on livestock production

Climate change and the uncertainty in the climate predictions do not exert a big influence on milk production, mortality rates (Fig. 10), or herd dynamics in general. Results for a typical farm in Stratum 2 (1–8 cattle) shown in Fig. 10 were very similar to the results for a typical farm in Stratum 3 (>8 cattle). Changes in stover yields under the various GCMs resulted in very minor reductions in annual milk production and slight increases in mortality rates (apart from GCM I). Apparently the predicted changes in stover production in the various climate change scenarios (Fig. 9a) were not large enough to be reflected in significant changes in livestock production.

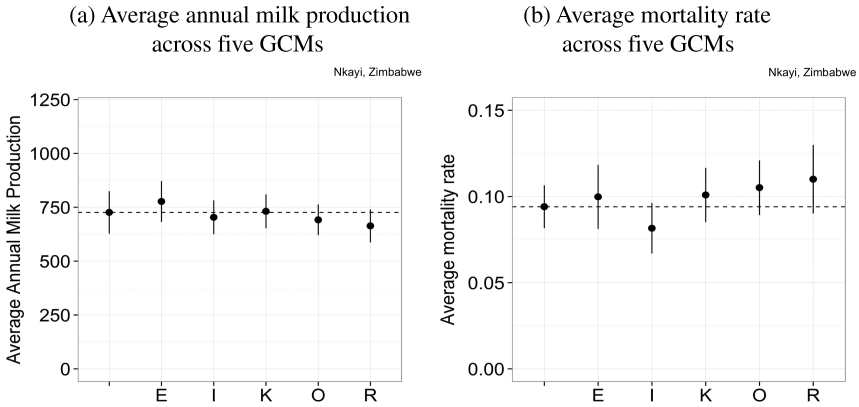


Fig. 10. Sensitivity of (a) milk production and (b) mortality rates to climate change for a representative farm in Stratum 2 in Nkayi, Zimbabwe. Five GCMs (denoted by their letters) are compared to baseline climate (1980–2010), represented by the first data-point and the dotted line. Dots represent average milk production and error bars the standard error around the mean across the 30 years of simulation.

Economic impact of climate change on current production systems

Here we assess the impact of climate change for current production systems. Figure 11 illustrates the projected percentage of farm households that lose from climate change, the percentage changes in the farm's net returns and *per capita* incomes, as well as the effects on poverty rates, for the different GCMs and also by farm type.

The results suggest that climate change impact varies in Nkayi, depending on the climate scenario. Under certain GCMs, especially GCM K, the wet scenario, more households (71%) tend to gain from climate change, while under others, especially GCM R, the dry scenario, more households (64%) tend to lose (Fig. 11).

The effect of climate change on the economic situation of the entire farm population is limited. The magnitude of gains and losses is relatively small, on average between –5% and 8% changes for the various economic indicators, including percentage change of farm net returns, percentage change of *per capita* incomes, and percentage change of poverty rates. Farm net returns of households without cattle can decrease by up to 10% (GCM R) or increase by up to 18% (GCM K). For those with large herds the returns decrease by up to 3% (GCM R) by or increase by up to 6% (GCM K). In absolute terms households lose up to 30 US$/farm (GCM R) or gain 50 US$/farm (GCM K). Households with large cattle herds lose most from climate change (between –50 and 90 US$ per farm net returns), as compared to those without cattle (between –10 and 20 US$ per farm net returns). *Per capita* income varies little among the household types.

The data also confirm that poverty is high in this community. According to this assessment, currently about 97% of the population lives on less than 1.25 US$ per

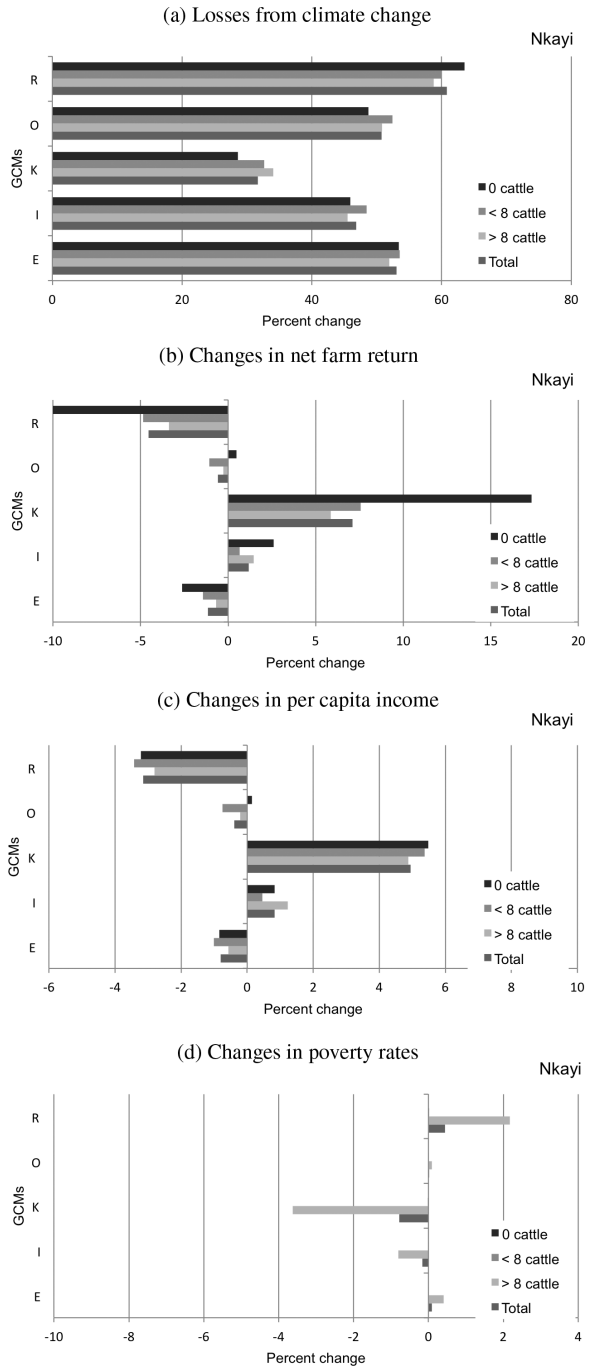


Fig. 11. Socio-economic indicators for estimating effects of climate change for current production systems: Percentages of potential losers from climate change, changes in farm net returns, changes in *per capita* income, and changes in poverty rates, by strata and climate model (GCMs R, O, K, I, and E).

person per day, most households live without or with only small cattle herds. Even with large herds, 91% of farm households are poor. Climate change does not change the proportion of households that are below the poverty line, on average between an increase of 1% and a decline of 1%. Farms with large cattle herds vary between an increase of poverty levels of 2% and a decline of 4%.

Core Question 2: What Is the Impact of Climate Change on Future Agricultural Production Systems?

Results and discussion

The impact of climate change on future agricultural farming systems in Nkayi is similar to that on the current farming systems, with slightly less negative influence than under current conditions (Fig. 12).

As for current production systems, climate change has limited influence on the economic situation of farm households for future production systems. Depending on the climate scenario, up to 67% of the households might gain from climate change (GCM K), or 64% might lose (GCM R). The magnitude of gains and losses (percentage change of farm net returns, percentage change of *per capita* incomes,

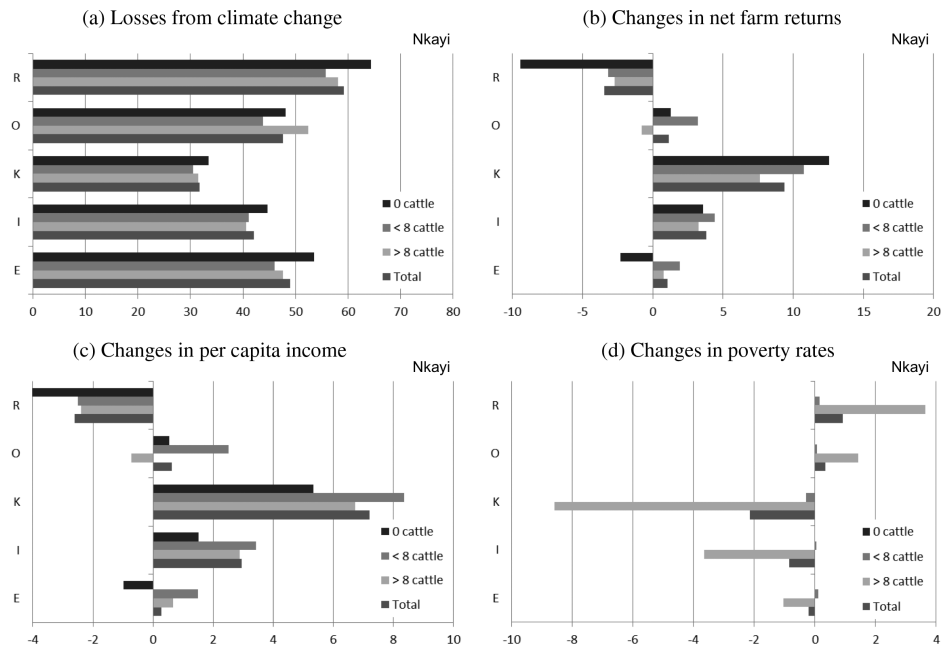


Fig. 12. Socio-economic indicators for estimating the effects of climate change for future production systems: Percentages of potential losers from climate change, changes in farm net returns, changes in *per capita* income, and changes in poverty rates, by strata and climate models (GCMs R, O, K, I, and E).

and percentage change of poverty rates) is also relatively small and varies between 4% loss and 9% gain for the various economic indicators. Those farms without cattle also experience greater changes in relative terms, between 10% loss and 13% gain. Those farms with large herds make greater gains in absolute terms, under GCM K up to 154 US$ per farm.

Despite the economic development, poverty rates are still high. About 90% of the population lives on less than 1.25 US$ per person per day, about 10% less than those under current production systems. Even with large herds, between 69% and 77% of farm households would be poor. Climate change does not much change the proportion of households above the poverty line of 1.25 US$ per person per day, while a large proportion of the farms will still be vulnerable to climate change. Across the total population poverty rates would change between 2% increase and 1% decline. Among the farms with large cattle herds, poverty rates would decline by 9% under GCM K and increase by 4% under GCM R.

Core Question 3: What Are the Benefits of Climate Change Adaptations?

Impact of adaptation on crop productivity

Benefits of organic and inorganic fertilizer application

Although the projected crop yield losses under the current farming practices are not substantial, use of soil amendments as adaptation strategies can offset the negative impact of climate change with mean yield gains ranging between 20% and 25% (Fig. 13). The use of organic amendments such as legume residues and low inorganic fertilizer application rates is less risky compared to high application of inorganic fertilizers. Application of high nitrogen fertilizers (recommended rate) shows very high variation over the years with yield changes ranging from –20 to >70%, while the use of lower rates (micro-dose) and use of legume residues (in this case mucuna) show lower variations, with yield changes ranging from –8% to >35% and –8% to >40 %, respectively. However, mean grain yields from the different treatments are similar, which shows that substantial benefits can be obtained from lower application rates, as increased temperatures and limited moisture would negatively affect crop production especially under high fertility treatments. In the study we used a maize–mucuna rotation system with application of 30% mucuna residues. The subsequent maize crop after mucuna would benefit from biological nitrogen fixation and also from the crop residues that are applied. Such adaptation strategies would benefit resource-poor farmers to improve main staple crop yields with minimal external inputs.

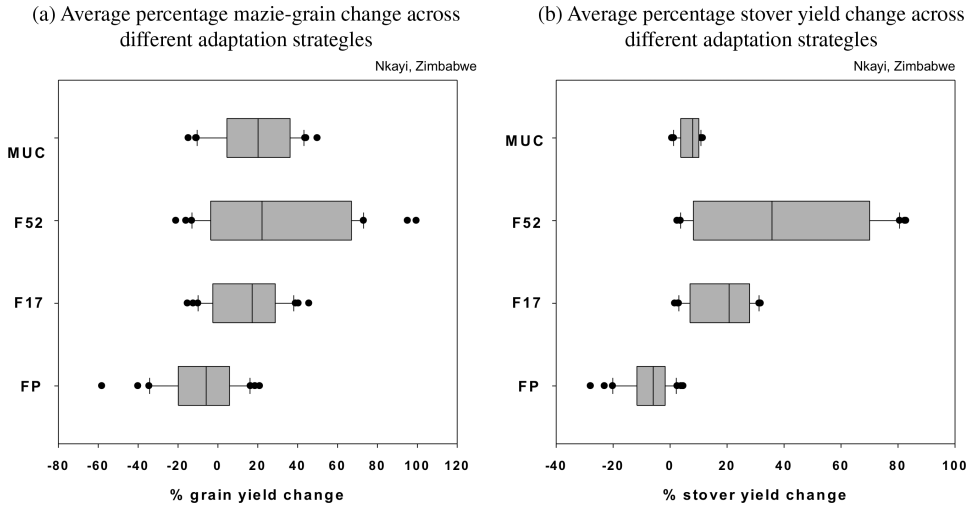


Fig. 13. Boxplots showing average percentage maize grain and stover yield change (five GCMs, mid-century, RCP 8.5) in Nkayi, Zimbabwe, under FP (farmer practice/no adaptation) and different adaptation strategies (F17: micro-dosing, F52: recommended fertilizer, MUC: maize–mucuna rotation system). The percentage change under adapted scenarios (F17, F52, and MUC) is calculated with respect to the non-adapted scenario under climate change while for the non-adapted scenario (FP) yield change is relative to FP under current climate.

Impact of adaptation on livestock production

Applying micro-dose fertilizer (F17) has a relatively minor effect on annual milk production for a typical farm with small cattle herds (1–8 cattle). The relative change fluctuates around the 0% line, except for a clearly positive change under GCM O (Fig. 14a). Under the recommended fertilizer application rate (F52) and the mucuna rotation (MUC) scenario, much clearer improvement in annual milk production are projected, around 20% and 25% improvement, respectively (Fig. 14a). With respect to mortality rates, the F17 scenario results in a strong improvement (decrease in mortality), which ranges from –20% to –50% change. However, with the F52 and MUC adaptations, an even stronger improvement can be achieved (Fig. 14b). The same trends were observed for a typical farm with large cattle herds, greater than eight cattle per household (not shown), even though the GCMs behave slightly differently than a farm with small cattle herds (in Fig. 10).

Impact of adaptation on farmer livelihoods

We first compared the effects of different fertilizer applications on farmers' livelihoods. According to the assumptions made in this analysis, the economic benefits from fertilizer applications are limited. The recommended fertilizer rates pay-off

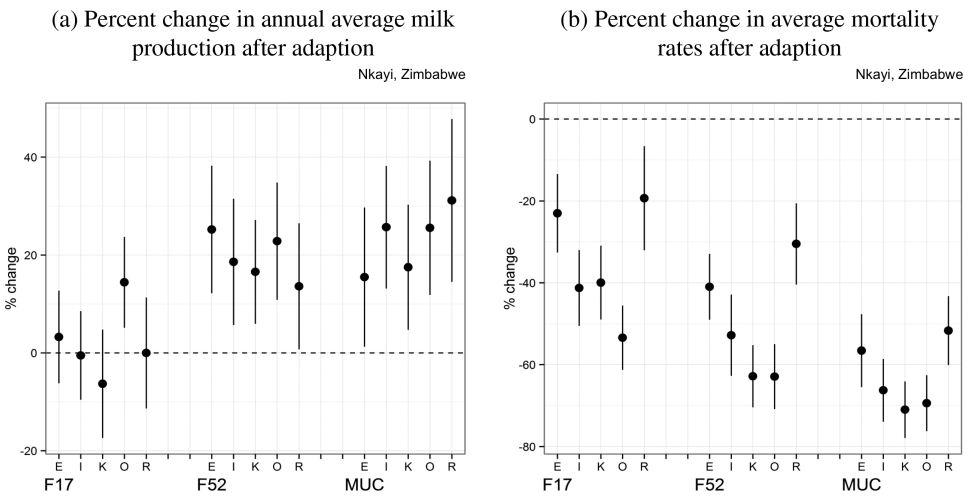


Fig. 14. Effect of adaptation options (F17: micro-dosing, F52: recommended fertilizer rate, MUC: mucuna rotation) on (a) annual milk production and (b) mortality rates for a medium farm in Nkayi, Zimbabwe. The percent change in the adapted scenario is calculated with respect to the non-adapted scenario in the future, with GCMs denoted by their letter. Dots represent the average change and error bars the standard error around the mean across the 30 years of the simulation.

under high-rainfall scenarios, through high yield increases for households with cattle. Under low-rainfall scenarios however, the low fertilizer application rates are more beneficial; especially poor households bear fewer costs and less risk.

In comparison, the maize–mucuna rotation is an alternative to fertilizer application for both high- and low-rainfall scenarios, but has its comparative advantage especially under low rainfall scenarios. Inclusion of mucuna is a low-cost/-risk alternative; especially poor households would adopt the technology and benefit from use of the organic fertilizer.

The adaptation package that was finally deemed appropriate for smallholder farmers under high-risk conditions comprised micro-dosing fertilizer application rates (F17) on one third of the farm's maize fields, a maize–mucuna rotation on the other two thirds, and switching to drought-tolerant maize with 10% to 18% yield increases. The following economic benefits can be expected (Table 10):

The adaptation package is likely to reduce vulnerability to climate change. Across the climate scenarios fewer households will be negatively affected by climate change. The proportion of households losing from climate change will possibly decrease, in ranges from 32% to 21% under the dry scenario GCM K or from 59% to 24% (GCM R). Almost 80% of the households will adopt the package. The adoption rates will be highest for households without cattle, assuming that they can convert the mucuna biomass to cash income.

Table 10. Socio-economic indicators and percentage changes in farm benefits from climate change adaptations for GCM K and GCM R.

	GCM K				GCMR			
Stratum	0 Cattle	1–8 Cattle	>8 Cattle	Total	0 Cattle	1–8 Cattle	>8 Cattle	Total
Adoption rates	95	69	73	79	94	65	72	76
Change in net returns	70	18	17	21	50	13	14	16
Change in *per capita* income	23	13	15	15	17	9	12	12
Change in poverty rate	0	−2	−18	−6	0	0	−14	−4

However, even though many households are likely to benefit, the magnitude of the benefits is relatively small. Farm net returns will increase by about 16% to 21%, and *per capita* incomes will increase by 12% to 15%. The overall poverty rate will be reduced by only 4% to 6%.

The economic benefits differ by farm types. Small farms without livestock make relatively little benefits from climate change adaptations. These farms might be adopting the technology package, but their benefits in absolute terms are rather small. Adopters make 100–180 US$ more farm net returns compared to non-adopters. The costs and benefits associated with the adaptation package tend to be more pronounced for larger farms. Adopters on medium (1–8 cattle) and better off farms (> 8 cattle) can increase their farm net returns from without adoption at about 900–1100 and 2000–2200 US$, to make with adoption higher net returns of 300–500 and 700–900 US$, respectively, but also face higher risk.

The selected adaptation package will not have a substantial impact on poverty levels. Overall poverty rates might be reduced by 4% to 6%. It will shift 14% to 18% of the larger farms to higher welfare levels, but not improve the welfare situation of the most vulnerable. For the majority of rural families, other solutions will have to be sought in and beyond agriculture.

In addition to the above we investigated food budgets (maize and other crops) for the different farm types under current and future production systems, and also under the adaptation package. Assuming food requirements of 120 kg maize per person per year, small farms without livestock can currently not cover their food needs from their own production. This food deficit will increase under climate change with and without the adaptation. The major challenge for these farmers is their high dependence on crop production, as long as no other income-generating activities are available to them. Small cropping areas, which are a consequence of limited labor and agricultural inputs and other factors, are a major constraint for them to increase production. These farmers will depend on safety support to sustain food security, unless functional markets will be developed that will allow them to sell high-value

crops and use parts of that income to buy food. Livestock owners, in comparison, will maintain small surplus of food production, under climate change and with the adaptation package. They can thus afford to convert some land for fodder production without undermining immediate food security. They can supplement food losses through livestock sales. It is important to note the role of other crops, which include small grains and legumes, as they contribute to household food security and nutrition.

Conclusions and Next Steps

Climate projections for Southern Africa have shown that temperatures are likely to increase by >2°C, rainfall will be varied, and evaporation will increase in response to increased temperature. Such changes will affect production of the main staple food, maize, in the medium and long term. If current farmer practice (low-to-zero application of soil amendments) were continued into the future, farmers would, in some years, experience yield reductions >20%, with a mean yield change reduction being –5%. Livestock play an important role in the current farming systems. The projected climate conditions can also reduce feed availability and consequently livestock production, though livestock performance seems to be less influenced by climate change than crop performance. Consequently, smallholder farmers that depend on rainfed agriculture will face greater food insecurity and vulnerability if substantial adaptation measures are not taken. When there is a crop failure there is no food available, and especially those without livestock (43%) will face increasing food deficits and would not be able to buy food even if it is available on the market. In absolute terms, the losses from climate change are highest for households with livestock and large farms. This is because the economic value of the farm activities by these households is far greater than that of the poor; with larger areas of croplands and herds the sum of losses through climate change outweighs those of poor households.

This study has shown that adaptation measures contribute to economic gains from intensification and diversification. The use of low rates of inorganic and organic fertilizer and inclusion of forage legume crops of high-quality feed biomass can substantially reduce the effects of climate change on crop and livestock production. Feeding livestock increases the economic returns from livestock. This generates economic benefits that would allow farmers to purchase staple food and thus supplement the food deficits. Households without livestock could use the higher returns on high-value crops (e.g., mucuna, but also other cash crops) as a way to sustain food security — provided that food and feed markets are functional. For larger farms with livestock investment in food, feed crops can offset negative effects of climate change and transition some farms to higher levels of production and welfare.

An important result of the integrated assessments about the high and possibly overestimated poverty levels in Nkayi, Zimbabwe. These are likely to prevail in

the future, if more drastic economic improvements are not made. National assessments in Zimbabwe (ZimVAC, 2013) acknowledge high poverty levels and food security in Nkayi (76% of the rural population below poverty line at <1.5 USD *per capita* expenditure per day; about 40% chronically food insecure). Reasons for overestimating poverty rates in this study could be that we did not take full account for off-farm activities. Other recent studies in Zimbabwe confirmed extremely low levels of cash income for the majority of the population (Dube *et al.*, 2014). Harris and Orr (2013) identified limited farm size and poor access to productive resources as major constraint for smallholder farmers raising income levels. Interventions that aim at improving the livelihoods of smallholder farmers in areas like Nkayi therefore have to go beyond food security and climate change adaptations, and capacitate farmers towards alternative livelihood activities. Alternative less risky, more profitable, and resilient products have to be identified and tested in the local context, e.g., livestock, cash crops, irrigation schemes. New initiatives shed light on the great potential and innovativeness of small and medium enterprises, which could facilitate farmer to market linkages from within the local context (Stepman *et al.*, 2014).

The RAP assessments set the bio-economic modeling results into the broader picture of economic development in Zimbabwe, based on current and future socio-economic trends. Stakeholders emphasized that government and agricultural policies will play a key role for promoting climate smart, resilient, and profitable agriculture in the future and that this has to go along with effective public and private investments in research and development. Stakeholders and farmers expressed a clear vision towards market-oriented agricultural production, supported by renewed investments in infrastructure and agricultural services and backed up by agricultural policies. Human population growth, which is associated with an increasing demand for quality food, was seen as a key driver for rural economic development. Product prices were not projected to increase much, given the interplay of increasing demand, higher production, and influx of cheaper imports. Similar trends are likely to be seen for inputs, increasing demand by a number of farmers, but also leading to revitalization of local processing industries.

The transition of the predominantly subsistence-oriented towards market-oriented smallholder farming system will, however, be slow, considering the existing challenges and barriers (e.g. low capital endowment, incomplete agricultural policy framework, need for institutional change to govern, regulate and enforceme). By addressing these as Anseeuw *et al.* (2013) suggest, future approaches will be oriented towards integration of the agricultural sector, by stepping out from subsistence towards economic development, promoting market linkages and limited-input support programs, with investments from both public and private sectors. Based on these assumptions, farmers will find incentives to invest in improved crop and livestock technologies. At the farm level, a switch from high risk towards more

diversified crop and livestock production and marketing, and better integration of livelihood activities on- and off-farm will reduce farmer vulnerability to climate-induced shocks such as dry spells, droughts, and flash floods as well as market shocks (e.g., price fluctuations). Improved integration on- and off-farm needs to go beyond technical options; there is a need to promote other pathways for sustainable low-cost and -risk intensification, supported by better integrated services and production-to-market linkages. As the results from climate change adaptation have shown, the interventions need to be tailored to farm type. Poor farmers can benefit from proactive and innovative investments in functional food and feed markets, and provide services beyond immediate food security. Larger farms can spearhead market-oriented production and sustain product flows.

Women will continue to play a critical role in farm management. Labor migration of men and high rates of female-headed households have contributed to women becoming important decision-makers on the farm, on issues of production, marketing, and sales of products. Recent ICRISAT studies have illustrated that women gained influence and knowledge with market-development processes, and were not marginalized as is often assumed. With more drastic changes there is new emphasis on gender-sensitive approaches to capacitate farmers to adapt and innovate, which ensure that women and men are involved in the full range of production to market activities.

At the community level, greater awareness of more extreme climatic conditions and a more integrated agricultural-development approach will be required in order not to aggravate possible negative impacts of climate change, but to lead to improved control and management of natural resources and land use. In the short term, despite investments in agriculture, the combination of increased population pressure, fragile environments, and poor institutional regulations will result in further degradation of soils, water, and landscape. Institutional and technological improvements, to govern, regulate, and enforce communal natural resource use will take time, but need to be established in the mid-term, to offset negative consequences of degradation (Siziba, personal communication).

The promotion of multi-stakeholder engagement will improve communication on context-specific investment opportunities, e.g., new attention to "marginal" crops and livestock, market requirements, and services needed.

Major message for stakeholders

For farmers to be more resilient in the future, policymakers need to understand the projected economic trends along with the impacts of climate change on farming systems, associated uncertainties, and favorable adaptation strategies. The major challenge in Zimbabwe is lack of expertise to generate such knowledge that can be

shared with decision-makers with regard to impacts of climate change on different sectors, including agriculture. Other challenges are how to convince decision-makers in the face of great uncertainties and how to bridge the gap between scientific and traditional perception of climate change (Tadesse, 2010).The approach we used in AgMIP was mainly aimed at addressing such issues as we engaged with stakeholders during the RAP development process for possible future production scenarios that would assist farmers in adapting and evaluating possible benefits across different farmer categories. It is therefore important for us to take another step and see how we could generate information that can also be used to support forecasting seasonal food production, famine early-warning systems, redefining agroecological zones and recommending adaptations that are specific for agroecological zones.

The AgMIP regional integrated assessments can also provide information about possible radical system shifts towards more productive and sustainable options, e.g., from maize–cattle systems towards more diversified maize–legumes–cattle–small-stock systems. Farmers can adapt to the impacts of climate change more specifically by changing management practices or crop choices, as well as considering other inputs such as chemical treatments and irrigation. It is important, however, for decision-makers to understand that there are conditions that need to be met such as input availability, access to markets with attractive prices, as well as infrastructure and functional institutions that would enable farmers to invest in agricultural production. Multi-stakeholder engagement in policy formulation is critical, to ensure the representation of interests and requirements by public and private sectors. More process-oriented planning and structured interactions among stakeholders is needed, with the goal of reconstructing the agricultural sector and transitioning to more resilient and profitable farming systems. Such planning processes should include a common vision as the foundation; technology choices informed by bio-economic models; functional markets to catalyze positive change; solutions based on farmers' choices and from within local contexts; and research and development to engage in those agricultural pathways.

References

Agricultural and Food Research Council (AFRC) (1993). *Energy and protein requirements of ruminants*, CAB International, Wallingford, UK.

Archer, E., Mukhala, E., Walker, S., Dilley, M., and Masamvu, K., (2007). Sustaining agricultural production and food security in Southern Africa: an improved role for climate prediction?, *Clim. Change*, **83**, 287–300.

Anseeuw, W., Kapuya, T., and Saruchera, D. (2013). Zimbabwe's agricultural reconstruction, Present state, ongoing projects and prospects for reinvestment, Development Planning Division Working Paper Series No. 32, Development Bank of Southern Africa and AgenceFrancaise Development, Halfway House.

Antle, J. (2011). Parsimonious multi-dimensional impact assessment, *Am. J. Agric. Econ.*, **93**(5), 1292–1311.

Antle, J. M. and Valdivia, R. O. (2011). *TOA-MD 5.0: Trade-off Analysis Model for Multi-Dimensional Impact Assessment*. Available at: http://trade-offs.oregonstate.edu. Accessed on 21 March 2014.

Bossio, D. (2009). Livestock and water: Understanding the context based on the 'Compressive Assessment of Water Management in Agriculture', *The Rangeland Journal*, **31**(2), 179–186.

Capo-chichi, L. J. A., Weaver, D. B., and Morton, C. M. (2002). "Agronomic and genetic attributes of Velvetbean (Mucuna sp): An excellent legume cover crop for use in sustainable agriculture", in van Saten, E. (ed.), *Making conservation tillage conventional: Building a future on 25 years of research*, Proceedings of 25th Annual Southern Conservation Tillage Conference for Sustainable Agriculture, Auburn, AL, USA.

Carberry, P., Gladwin, C., and Twomlow, S., (2004). "Linking simulation modeling to participatory research in smallholder farming systems", in Delve, R. J. and Probert, M. E. (eds.), *Modelling Nutrient Management in Tropical Cropping Systems*, *Proc. ACIAR*, 114, pp. 32–46.

Conrad, H. R. (1966). Symposium on factors influencing voluntary intake of herbage by ruminants — physiological and physical factors limiting feed intake, *J. Anim. Sci.*, **25**, 227–243.

Dimes, J., Cooper, P., and Rao, K. P. C. (2008). Climate change impact on crop productivity in the semi-arid tropics of Zimbabwe in the 21st century, *Proc. Workshop on Increasing the Productivity and Sustainability of Rainfed Cropping Systems of Poor, Smallholder Farmers*, Tamale, Ghana, 22–25 September 2008.

Dorward, A., Poole, N., Morrison, J. Kydd, J., and Urey, I. (2003). Markets, institutions and technology: missing links in livelihood analysis, *Development and Policy Review*, **21**(3), 319–332.

Dube, T., Homann-Kee Tui, S., van Rooyen, A., and Rodriguez, D. (2014). Baseline and situation analysis report: Integrating crop and livestock production for improved food security and livelihoods in rural Zimbabwe (unpublished), ICRISAT Report, Bulawayo.

Ingram, J. and Ainslie, A. (2011). *What are scenarios and how can they be helpful for thinking about agriculture and food security in the future?* Available at: www.slideshare.net/cgiarclimate/developing-ccafs-scenarios-7728794. Accessed on 21 March 2014.

International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) (2012). Stock feed use by smallholder farmers in Gwanda, Household survey, Gwanda District, Zimbabwe.

Harris, D. and Orr, A. (2013). Is rainfed agriculture really a pathway from poverty?, *Agric. Syst.*, **123**, 84–96.

Homann, S., van Rooyen, A., Moyo, T., and Nengomasha, Z. (2007). Goat production and marketing: Baseline information for semi-arid Zimbabwe, International Crops Research Institute for the Semi-Arid Tropics.

Homann-KeeTui, S., Bandason, E., Maute, F., Nkomboni, D., Mpofu, N., Tanganyika, J., Van Rooyen, A.F., Gondwe, T., Dias, P., Ncube, S., Moyo, S., Hendricks, S., and Nisrane, F. (2013). Optimizing Livelihood and Environmental Benefits from Crop Residues in Smallholder Crop-Livestock Systems in Southern Africa, *ICRISAT Socio-economics Discussion Paper Series*, Series Paper Number 11.

Jones, N. A., Perez, P., Measham, T. G., Kelly, G. J., D'Aquino, P., Daniell, K., Dray, A., and Ferrand, N. (2008). Evaluating participatory modelling: Developing a framework for cross-case analysis, Socio-Economics and the Environment in Discussion, CSIRO Working Paper Series, 2008–2011.

Jones, P. G. and Thornton, P. K. (2003). The potential impacts of climate change in tropical agriculture: the case of maize in Africa and Latin America in 2055, *Global Environmental Change*, **13**, 51–59.

Kandji, T. S., Verchot, L., and Mackensen, J. (2006). *Climate change and variability in Southern Africa: Impacts and adaptation in the agricultural sector*, World Agroforestry Centre and United Nations Environment Programme Report, p. 42.

Konandreas, P. A. and Anderson, F. M. (1982). *Cattle Herd Dynamics: An Integer and Stochastic Model for Evaluating Production Alternatives*, ILCA Research Report 2, ILCA Publications, Addis Ababa.

Masikati, P. (2011). *Improving the Water Productivity of Integrated Crop-livestock Systems in the Semi-arid Tropics of Zimbabwe: Ex-ante Analysis Using Simulation Modeling*, PhD thesis, ZEF, Bonn.

Masikati, P., Manschadi, A., van Rooyen, A., and Hargreaves J. (2013). Maize–mucuna rotation: an technology to improve water productivity in smallholder farming systems. *Agric. Syst.*, 123, 62–70.

Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture, *PNAS*, **104**(50), 19680–19685.

Naab, J., Bationo, A., Wafula, B. M., Traore, P. S., Zougmore, R., Outtara, M., Tabo, R., and Vlek, P. L. G. (2012). "African perspective on climate change and agriculture: Impacts, adaptation and mitigation potential", in Hillel, D. and Rosenzweig, C. (eds.), *Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications*, Imperial College Press, London, pp. 103–124.

Nin Pratt, A. and Diao, X. (2008). Exploring Growth Linkages and Market Opportunities for Agriculture in Southern Africa, *J. Econ. Integr.*, **23**(1), 104–137.

Peden, D.,Taddesse, G., and Haileslassie, A. (2009). Livestock water productivity: Implications for sub- Saharan Africa, *The Rangeland Journal*, **37**, 187–193.

Powell, J. M., Pearson, R. A., and Hiernaux, P. H. (2004). Review and interpretation. Crop-livestock interactions in the West African Drylands, *Agron. J.*, **96**, 469–483.

Pretty, J. N. (1995). Participatory learning for sustainable agriculture, *World Development 23*, 1247–1263.

Rouault, M. and Richard, Y. (2005). Intensity and spatial extent of droughts in Southern Africa, *Geophysical Research Letters*, **32**, L15702.

Reason C. and Jagadheesha D. (2005). A model investigation of recent ENSO impacts over Southern Africa, *Meteorol. Atmos. Phys.*, **89**, 181–205.

Rockström, J., Barron, J., and Fox, P. (2003). "Water productivity in rain-fed agriculture: challenges and opportunity for smallholder farmers in drought-prone tropical agro-ecosystems", in Kijne, J. W., Barker, R., and Molden D. (eds.), *Water Productivity in Agriculture: Limits and Opportunities for Improvement*, CAB International, pp. 145–162.

Rosenzweig, C., Jones, J., Hatfield, J., and Antle, J. (2014). *Guide for Regional Integrated Assessments: Handbook of methods and procedures (v5)*. Available at: http://www.agmip.org/wp-content/uploads/2013/10/AgMIP-Regional-Integrated-Assessment-Handbook-v5.pdf. Accessed on 21 March 2014.

Ruane, A. C., Goldberg, R., and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and hisorical climate series estimation. *Agr. Forest Meteorol.*, 200. doi: 10.1016/j.agrformet.2014.09.016.

Rufino, M. (2008). *Quantifying the contribution of crop-livestock integration to African farming*, PhD thesis, Wageningen UR, the Netherlands.

Rufino M. C., Herrero, M., van Wijk, M. T., Hemerik, L., de Ridder, N., and Giller, K. E. (2009). Lifetime productivity of dairy cows in smallholder farming systems of the highlands of Central Kenya, *Animal*, **3**, 1044–1056.

Rufino, M. C., Dury, J., Tittonell, P., van Wijk, M. T., Herrero, M., Zingore, S., Mapfumo, P., and Giller, K. E. (2011). Competing use of organic resources village-level interactions between farm types and climate variability in a communal area of NE Zimbabwe, *Agric. Syst.*, **104**, 175–190.

Stepman, F. (2014). Programming SMEs in ARD. Presentation at Agrinatura Science days, 5–8 May, 2014, Vienna. Available at: http://www.agrinatura.eu/Activities-Projects/AGRINATURA-SCIENCE-DAYS/Programme/List-of-presentations/. Accessed on 21 March 2014.

Tadesse, D. (2010). The impact of climate change in Africa, *Institute for Security Studies*, 220.

Thornton, P. K., van de Steeg, J., Noterbaert, A., and Herrero, M. (2009). The impacts of climate change on livestock and livestock systems in developing countries: A review of what we know and what we need to know, *Agricultural Systems*, **101**, 113–127.

Walker, N. J. and Schulze, R. E., (2008). Climate change impacts on agro-ecosystem sustainability across three climate regions in the maize belt of South Africa, *Agric., Ecosyst. Environ.*, **124**, 114–124.

Walker, S., Nanja, D., Gondwe, P., and Dimes, J. (2009). "Mujika community climate — cropping systems modelling exercise", in Van Ittersum, M. K., Wolf, J., and Van Laar, H. H. (eds.), *Proceedings of the Conference on Integrated Assessment of Agriculture and Sustainable Development: Setting the Agenda for Science and Policy (AgSAP 2009)*, Egmondaan Zee, the Netherlands, 10–12 March 2009, Wageningen University and Research Centre, Wageningen, pp. 432–433.

Williams, T. O., Thornton, P., and Fernandez-Rivera, S. (2002). "Trends and prospects for livestock systems the semi-arid tropics of Sub-Saharan Africa", in *Targeting Agricultural Research for Development in Semi-Arid Tropics of Sub-Saharan Africa*, Proceedings held at International Center for Research in Agroforestry Nairobi, Kenya, 1–3 July 2002, pp. 155–172.

World Bank (2009). Making development climate resilient: A World Bank strategy for Sub-Saharan Africa, Report No. 46947 — AFR.

ZimVAC (2013). *Rural livelihoods assessment*, Harare.

Section II

South Asia

This page intentionally left blank

Chapter 6

Integrated Assessments of the Impact of Climate Change on Agriculture: An Overview of AgMIP Regional Research in South Asia

Sonali P. McDermid[1,2], Guntuku Dileepkumar[3], K. M. Dakshina Murthy[3], S. Nedumaran[3], Piara Singh[3], Chukka Srinivasa[5], B. Gangwar[6], N. Subash[6], Ashfaq Ahmad[7], Lareef Zubair[8,9], and S. P. Nissanka[8]

[1]*The NASA Goddard Institute for Space Studies, New York, NY, USA*

[2]*NASA Postdoctoral Program and Oak Ridge Associated Universities, Oak Ridge, TN, USA*

[3]*The International Crops Research Institute for the Semi-Arid Tropics, Hyderabad, India*

[4]*The Acharya N. G. Ranga Agricultural University, Hyderabad, India*

[5]*Tamil Nadu Agricultural University, Coimbatore, India*

[6]*The Indian Council on Agricultural Research, New Delhi, India*

[7]*University of Agriculture, Faisalabad, Pakistan*

[8]*University of Peradeniya, Peradeniya, Sri Lanka*

[9]*Foundation for Environment, Climate and Technology, Digana Village, Rajawella*

Introduction

South Asia encompasses a wide and highly varied geographic region, and includes climate zones ranging from the mountainous Himalayan territory to the tropical lowland and coastal zones along alluvial floodplains. The region's climate is dominated by a monsoonal circulation that heralds the arrival of seasonal rainfall, upon which much of the regional agriculture relies (Mall *et al.*, 2006). The spatial and temporal distribution of this rainfall is, however, not uniform over the region. Northern South Asia, central India, and the west coast receive much of their rainfall during

the southwest monsoon season, between June and September. These rains partly result from the moisture transport accompanying the monsoonal winds, which move in the southwesterly direction from the equatorial Indian Ocean. Regions further south, such as south/southeast India and Sri Lanka, may receive rains both from the southwest monsoon, and also during the northeast monsoon season between October and December (with northeasterly monsoonal wind flow and moisture flux), which results in a bi- or multi-modal rainfall distribution. In addition, rainfall across South Asia displays a large amount of intraseasonal and interannual variability (Fig. 1). Interannual variability is influenced by many drivers, both natural (e.g., El Niño Southern Oscillation; ENSO) and man-made (e.g., rising temperatures due to increasing greenhouse gas concentrations), and it is challenging to obtaining accurate time-series of annual rainfall, even amongst various observed data products, which display inconsistencies amongst themselves (exemplified in Fig. 1). These climatic and rainfall variations can further complicate South Asia's agricultural and water management.

Agriculture employs at least 65% of the workforce in most South Asian countries, and nearly 80% of South Asia's poor inhabit rural areas. Understanding the response of current agricultural production to climate variability and future climate change is of utmost importance in securing food and livelihoods for South Asia's growing population. In order to assess the future of food and livelihood security across South Asia, the Agricultural Model Intercomparison and Improvement Project (AgMIP) has undertaken integrated climate-crop-economic assessments of the impact of climate change on food security and poverty in South Asia, encompassing Bangladesh, India, Nepal, Pakistan, and Sri Lanka (Rosenzweig *et al.*, 2013). AgMIP has funded, on a competitive basis, four South Asian regional research teams (RRTs) and one South Asian coordination team (CT) to undertake climate-crop-economic integrated assessments of food security for many districts in each of these countries, with the goal of characterizing the state of food security and poverty across the region, and projecting how these are subject to change under future climate conditions.

Understanding the historical production trends and the impact of observed farming practices in South Asia are crucial to successfully plan for, and adapt, food production under future climate conditions. South Asia benefitted from a boom in food grain productivity in the 1970s as a result of "green revolution" technologies and high-yielding seed varieties (Hazel *et al.*, 2008). However, as the population has continued to rise, and as other non-agricultural sectors have developed, South Asia is at risk of not being able to provide sustained food and nutrition security in the future. In fact, some studies point to a seeming "plateau" of food grain production in various areas that suggest current technology trends may not be sustainable without

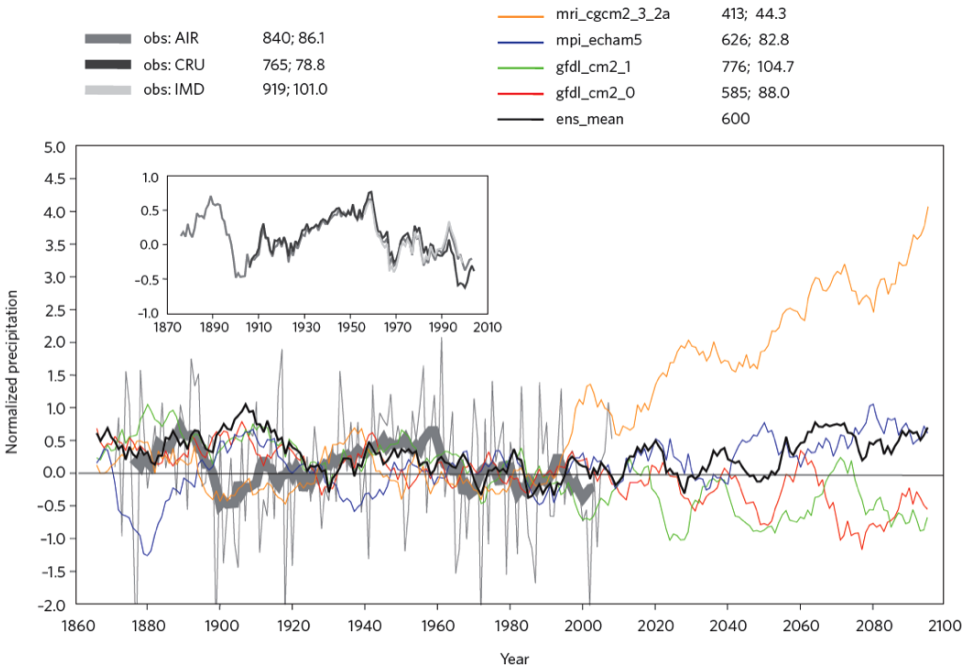


Fig. 1. Historical and SRES A1B projection of South Asian monsoon rainfall (Turner and Annamalai, 2012). Time-series of mean summer (June to September) rainfall averaged over the South Asian domain from 1861–2100. Four climate models are shown (colored lines), along with gauge information from the 1871–2008 AIR index (shown in the thick gray line in the main plot). The inset shows the AIR index compared to the 1951–2004 IMD daily gridded data and 1901–2009 monthly gridded CRU data. All curves are normalized by their mean and standard deviation, measured over the 1961–1999 period and are passed through an 11-year moving window. Reprinted by permission from Macmillan Publishers Ltd: *Nature Climate Change*, Turner, A. G., Annamalai, M., Climate change and the South Asian Summer Monsoon, **2**(8), copyright 2012.

substantial improvements in seed, management, and agricultural planning into the future (Grassini *et al.*, 2013). Furthermore, green revolution practices contributed to the over-utilization of fertilizers, pesticides, and resources, while diminishing soil quality and biodiversity. Poverty and malnutrition also persist, even in the face of increased grain production and stores.

In particular, these production increases over the 20th century have also encouraged the increasing use of groundwater stores, which has resulted in the over-exploitation of important ground aquifers. These aquifers are in jeopardy of running dry in what are now some of the most productive areas in South Asia, particularly in Pakistan and northwest India (Rodell *et al.*, 2009). The concurrent land-use transition, deforestation, loss of soil health, and the flight of the agricultural workforce to urban areas are also compounding factors that must be considered when planning for future agriculture and resource policies.

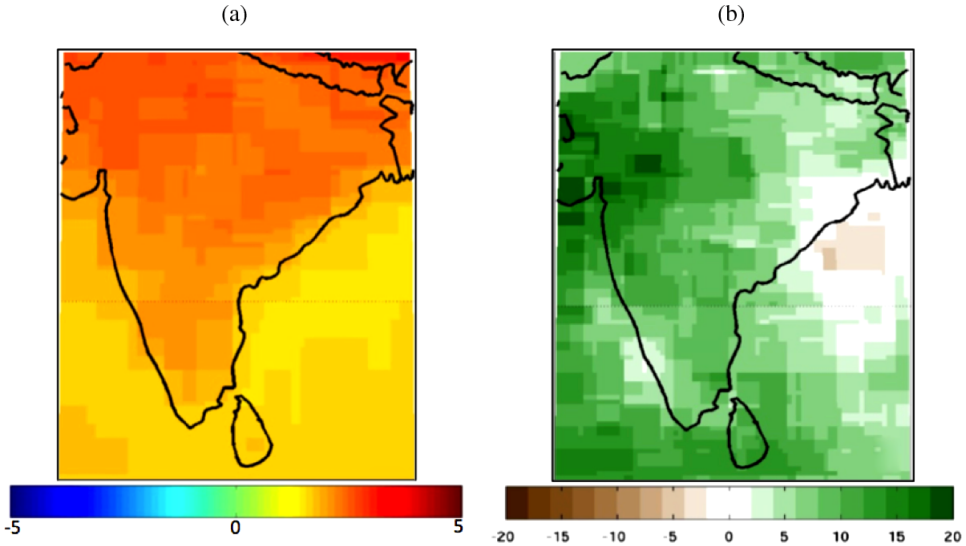


Fig. 2. Temperature (a, °C) and precipitation (b, %) changes under RCP8.5 mid-century climate projections from 20 CMIP5-coupled global-climate models, compared to baseline conditions. Courtesy of Alexander Ruane and CMIP5.

Potential Climate Change Impacts in South Asia

Further compounding these concerns are the changes expected to occur with rising global carbon emissions as the 21st century progresses. Climate change is expected to raise baseline mean, minimum, and maximum temperatures, bringing a moderate-to-large warming across the entire region by mid-century (Kirtman *et al.*, 2013), and also raise sea levels in vulnerable coastal territories. In addition, climate change may impact the strength of the regional monsoon circulation and the timing, frequency, and spatial distribution of seasonal rainfall, although large uncertainties exist in quantifying these changes (Turner and Annamalai, 2012). Figure 2 shows the IPCC climate models' projections of future interannual rainfall up to 2100, and there are substantial differences in both the interannual variability and the amount of rainfall projected. Bracketing this uncertainty will be critical for assessing impacts to future agricultural production. In addition to this, some other prime concerns amongst stakeholders in South Asia include potential increases in extreme events, more variability in rainfall, pronounced dry periods, inadequate or limited rainfall during the monsoon onset, and rising minimum and wintertime temperatures (Mall *et al.*, 2006).

AgMIP has attempted to characterize climate change and vulnerability in geographically varied South Asian subregions, challenging areas in which to project climate changes as climate models have historically had difficulty resolving fine-scale geographic features and dynamical processes. A major objective of the AgMIP

South Asia regional assessments studies is to assess how important crops respond to climatic changes in temperature, rainfall, and humidity variables, and to project what the future impact might be to crop yields, prices, poverty levels, and overall farmer livelihoods under a range of future climate and economic scenarios.

Regional Contrasts

South Asia's climate can be generally characterized by a monsoonal regime, in which the main rains occur during either the southwest or the northeast phases of the monsoon (for South India and Sri Lanka). However, the region is highly varied in terms of topography (Fig. 3), hydrology, and soils which make for diverse agricultural systems, and climate impacts. These regional distinctions will be further characterized in the following chapters with depictions of the farming systems being modeled.

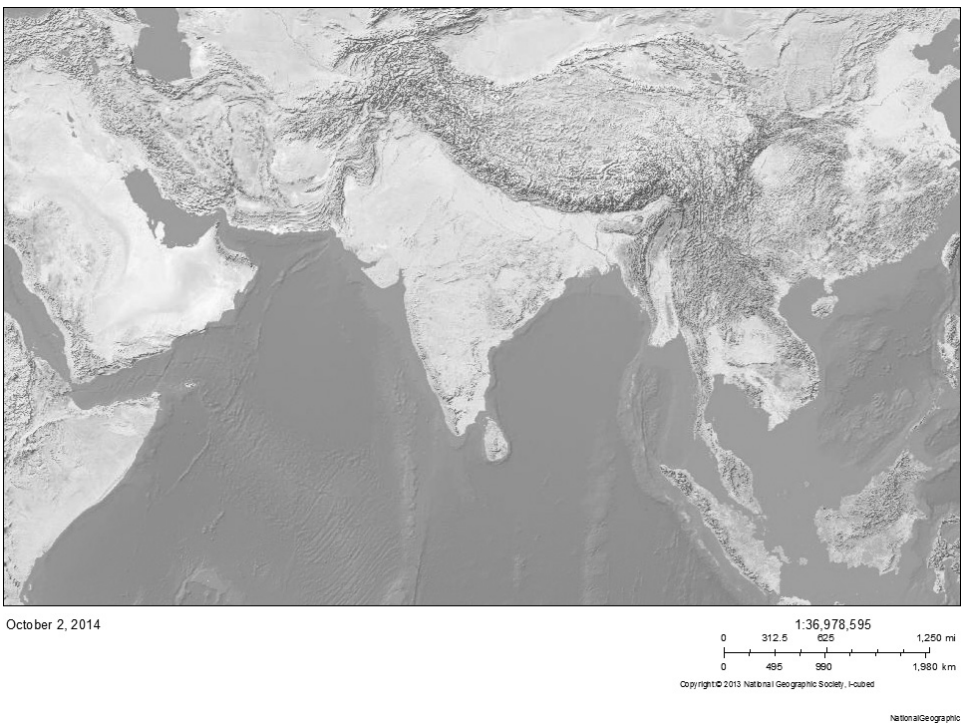


Fig. 3. The topography and geography of the South Asian region. The monsoon rains bring the sub-Himalayan and northwest regions the majority of their rainfall, largely distributed from June to September. South India and Sri Lanka also benefit from the second phase of the monsoon (the northeast monsoon), which is prevalent from October to November.

Pakistan

Pakistan's climate spans from subtropical arid to semi-arid, temperate to alpine, and rainfall totals across the country can span 100 to 2000 mm, and the majority of which occurs from June to September (Franken, 2012; Kahlown and Majeed, 2002). Nearly 40% of the population of Pakistan participates in the agricultural sector, in which the dominant crops are wheat, rice, and cotton (GOP, 2011, 2012). Within Pakistan, these crops are grown in different agroecological zones, each comprising a diversity of soil, hydrological, climatic, and even social, conditions. The Punjab region dominates the agricultural production such that much of the country's agricultural regions are more homogeneous than the wider country. There are two primary growing seasons in Pakistan, and rainfed agriculture is heavily dependent on the southwest monsoon, which has historically been subject to a large amount of variability in the timing and amount of rainfall (Ringler and Anwar, 2013). Additionally, significant pressure has been applied to water management and resources due to the increasing prevalence of cash crops, population growth, urban growth, and other competing sectors.

The Indo-Gangetic Basin (India, Nepal, Bangladesh)

The Indo-Gangetic Basin (IGB) has historically seen high variability in monsoon rainfall and extreme events across the region, due to the east–west movement of low-pressure centers along the trough that overlies the subregion (Turner and Annamalai, 2012). Additionally, the continuation of glacial melt may eventually result in decreases in river flow, which is a primary irrigation resource, particularly in east IGB. The west IGB is characterized by having a more developed irrigation infrastructure and relies heavily on the extraction of groundwater for crop irrigation. While this may currently insulate western IGB farmers from the irregularities of the southwest monsoonal rainfall, the over-exploitation of these groundwater resources may result in eventual decreases in wheat and rice production as water stores run low (Rodell *et al.*, 2009). Additionally, other indirect climate change effects may compound impacts on agriculture. A comprehensive study by Ruane *et al.* (2013) investigated climate-related rises in temperature and CO_2 concentrations, changes in rainfall, impacts of river flooding, and sea-level rise on agricultural production in Bangladesh. The study identified key vulnerabilities of Bangladesh's agricultural system, and in particular rice production, under future changes in rainfall, sea-level rise, which can inundate and salinate coastal agricultural lands, and river flooding.

South India

The South India AgMIP region encompasses the Indian states of Andhra Pradesh and Tamil Nadu. Although considered one region in the AgMIP assessments, these

two states have distinctive rainfall seasons, topography, soils, etc. Andhra Pradesh receives most of its rainfall during the southwest monsoon season, while Tamil Nadu receives rainfall during both the southwest monsoon and northeast monsoon (although most of the rainfall occurs during the northeast monsoon). Though uncertainty exists, climate projections indicate that seasonal rainfall totals may increase across south India (Turner and Annamalai, 2012). In Andhra Pradesh, agriculture provides a livelihood for nearly 65% of the population, and nearly half of the cultivated land in Andhra Pradesh is irrigated, while half is rainfed. Approximately half of Tamil Nadu's geographical area is devoted to agriculture, while nearly two thirds of the population is employed in the agricultural sector. Both Andhra Pradesh and Tamil Nadu have long coastlines to enable export, and have the capability to further develop their agricultural sector. Maize and rice are among the most important crops in both Andhra Pradesh and Tamil Nadu, and will be a focus of AgMIP integrated assessments.

Sri Lanka

Sri Lanka is characterized by high subregional annual rainfall totals, and low temperature variability, which can enable a relatively high state of food security, despite internal variability in the timing and active/break periods of rainfall during the rainy seasons. A majority of the rainfall occurs during the Yala and Maha seasons, which correspond to the southwest and northeast monsoons. Agriculture accounts for nearly one third of the labor force, and rice is among the most important food crops planted in a variety of regions. Sri Lanka's rice, and overall agricultural production, is susceptible to climate shocks, which has implications for domestic food prices (Yahiya *et al.*, 2011; Zubair, 2002, 2005). Global climate models generally indicate wetter conditions over Sri Lanka, but there is uncertainty in the projections of extreme rainfall events and temperature variability, particularly at the district level (Turner and Annamalai, 2012). Additionally, sea-level rise could impact coastal rice growing communities.

Integrated Assessments of Food Security in South Asia

Sustainable agricultural production must focus not just on productivity of food grains, but must also consider the natural resource management, market externalities, inclusion of high-value crops and livestock options, agroforestry, agricultural intensification on existing lands, and other more broad socio-economic problems (micro-nutrient fortification and pro-rural policies; Hazel *et al.*, 2008). Such considerations must and can be included through the use of interdisciplinary, integrated assessments of the impact of global environmental and socio-economic change on

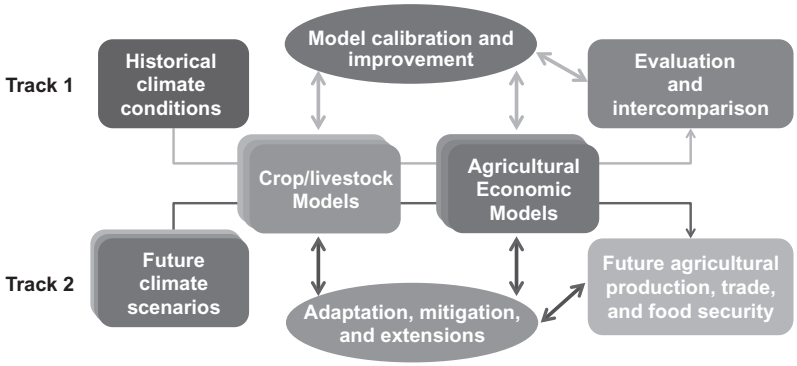


Fig. 4. The AgMIP framework for integrated assessments of the impact of climate change on agriculture. Reprinted from Rosenzweig *et al.* (2013) with permission from Elsevier.

regional agriculture. Though there have been many assessments of future agricultural production in various South Asian states (e.g., Knox *et al.*, 2012, and references therein), there is much scope for a comprehensive climate-crop-economic assessment that investigates the impact of climate change on overall food security, farmer income, and poverty. AgMIP presents a unique approach in integrated assessment by combining multi-model intercomparisons with interdisciplinary (climate-crop-economic) interactions that facilitate such a comprehensive investigation of the impact of climate change on agriculture. Additionally, AgMIP has involved a range of stakeholders at various local and regional levels to inform these integrated assessments, and have worked with South Asian RRTs to develop and test the efficacy of various adaptation strategies, given different scenarios of climatic and socio-economic change.

The AgMIP framework (Fig. 4) utilizes a two-track approach to understand and attribute historical fluctuations in agricultural production, intercompare and improve the crop and economic models, evaluate future impacts to food security, and develop and test adaptation strategies (Rosenzweig *et al.*, 2013). Additionally, AgMIP has a range of cross-cutting initiatives, particularly to evaluate the uncertainty in these assessments for informing stakeholders and decision-makers. The climate models utilized are represented in the Intergovernmental Panel on Climate Change Fifth Assessment Report (AR5) (Kirtman *et al.*, 2013). There are four AgMIP RRTs in South Asia comprised of climate scientists, crop scientists, agroeconomists, and information technology experts. These teams are tasked with carrying out integrated assessments of food security utilizing the AgMIP Protocols (Rosenzweig *et al.*, 2013) in specified districts across the region (black dots, Fig. 5), and their researchers hail from Pakistan, India, Nepal, Bangladesh, and Sri Lanka. These teams mainly conduct their crop simulations with the Decision Support System for

Fig. 5. AgMIP focus regions in South Asia (courtesy of AgMIP).

Agrotechnology Transfer (DSSAT; Jones *et al.*, 2003; Hoogenboom *et al.*, 2012), the Agricultural Production Systems Simulator (APSIM; Keating *et al.*, 2003), and Infocrop (Aggarwal, 2006). All the RRTs utilize the Tradeoff Analysis Minimum Data Model (TOA-MD; Antle *et al.*, 2011) for their agroeconomic assessments of climate impacts and economic effects across a representative population of farmers in each South Asian focus region.

Identifying and integrating stakeholder concerns

Given the variety of concerns facing South Asian agriculture in the 21st Century, the AgMIP RRTs' climate-crop-economic integrated assessments can help to identify the most critical parameters for assessing agricultural production, bracket the uncertainty in future climate changes, and aid in developing adaptation strategies that target South Asia's diversity of agricultural districts, while serving to promote food security across the region. The South Asian RRTs have engaged a range of

stakeholders, from the federal ministry level to district-level extension specialists, and even farmers. Each stakeholder meeting conducted by the RRTs has had a multi-fold objective: To communicate the results and findings from the integrated assessments, and to work with the various stakeholders to frame the outstanding challenges to agriculture which can be targeted through the AgMIP framework. In this way, the stakeholders have become important participants in the AgMIP process, particularly with respect to development of future agricultural trajectories, classified as "representative agricultural pathways", described below. In order to best address stakeholder concerns and consider the future of agricultural systems in these regions, AgMIP regional research focuses on answering three core questions:

(1) What is the sensitivity of current agricultural production systems to climate change?
(2) What is the impact of climate change on future agricultural production systems?
(3) What are the benefits of climate change adaptations?

Representative agricultural pathways (RAPs)

The future state of regional food security can be influenced by multiple drivers of change: Climatic, socio-economic, and geo-political. Although there are uncertainties in the future trajectories of these drivers, their inclusion in AgMIP integrated assessments is critical in order to develop regionally tailored adaptation strategies. Therefore, the AgMIP RRTs have engaged stakeholders at multiple levels (representing farmers, districts, states, and federal entities) to jointly develop representative agricultural pathways (RAPs). These RAPs will provide agricultural development scenarios in the joint context of the representative concentration pathways of carbon emissions and the shared socio-economic pathways of international development (Rosenzweig *et al.*, 2013). Additionally, the regional teams will devise adaptation strategies through consultation with stakeholders, and these will be incorporated into the future RAPs to inform the integrated assessments. Many adaptation strategies in the subregions will focus on diversifying farm income strategies, involving multiple or alternative crops, incorporating livestock, or improving water saving, storage and service techniques. These have been recommended as suitable strategies to pursue in these regions (Morton, 2007).

The RAPs are informed through AgMIP global economic initiatives and incorporate important drivers of global food and agricultural input markets and prices. This is done by incorporating trajectories based upon assumptions such as "business as usual". Since RAPs are statements about the likely evolution of variables such as soil fertility, farm size, and regulatory policies, their development requires interactions with informed stakeholders to make them regionally representative. All the South

Asian RRTs have conducted a number of RAP development workshops with stakeholders, the results of which are detailed in Part 2, Chapters 7–10 in this volume. In addition to aiding the RAP development workshops, facilitating and enhancing the communication and presentation of AgMIP data and findings to major stakeholders has been a key priority for the regional coordination team (CT). The AgMIP South Asia CT activities are detailed below.

Information-Sharing and Stakeholder Engagement

In this first phase of the AgMIP RRT assessments, the South Asia CT contributions have facilitated (1) enhanced capacities through training of the South Asian RRTs, as well as national agriculture and natural resource management agencies; (2) outreach and dissemination of key RRT findings through engagement and coordination of stakeholders. The CT team encourages the continued development of knowledge-sharing platforms to enable learning exchanges among and across the various AgMIP regional teams of South Asia, national research programs, and other stakeholders who utilize AgMIP research results.

Training

The CT was responsible for coordination and facilitation of region-wide workshops and training sessions, in collaboration with the AgMIP leadership team. This included the multiple crop model training workshop, which provided experienced crop modelers with training on a second crop model for use in the AgMIP regional integrated assessments (see also Part 2, Chapter 13 and Appendix 1 in this volume). Plenary sessions of workshop proceedings were recorded by video for sharing with researchers elsewhere. The sessions document RRT experiences in adoption of a second crop model, uses of AgMIP IT tools, and methods for assessing and interpreting the multiple crop model simulations.

The CT also organized virtual training experiences, including AgMIP climate, crop, and economic output analysis and interpretation webinars. Six virtual meetings were conducted by utilizing KSIConnect, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)'s virtual knowledge platform. A section of the platform was dedicated to serve AgMIP and its RRTs. This allowed collaborative virtual experiences and sharing of research results. The webinars made possible through these virtual interactions helped the RRT members to interpret their data better and to draw valuable conclusions, which are discussed in other chapters of this volume.

The CT also created innovative demonstration "knowledge products" to stimulate interactivity, to motivate further collaboration across existing RRT initiatives, and

to broaden engagement to include other researchers and stakeholders in the region. Demonstration products of the CT included the below prototypes:

- Data repositories with well-defined metadata features to store, back-up, and share data and statistical analyses of those data by incorporation of open-source statistical software. The repository encourages researchers to store data in a secured online location by providing useful tools for quick investigations of data attributes, trends, or distributions without installing statistical software on their respective desktops.
- Online cloud-based tool for data aggregation, analysis, and visualization, including features to help researchers to share results with others.
- Web GIS platform for map generations and to aid spatial data interpretation. The prototype was developed in collaboration with the East Africa RRT and demonstrates how users could jointly access high-quality figures, images of AgMIP integrated assessment results, and characterizations of the distribution of climate impacts in the South Asian subregions. The CT also explored spatial integration with Google Maps for inclusion of auxiliary project information, research results/analysis, outputs, lessons learned, and impact videos and photo galleries.

Stakeholder engagement

The South Asia CT also played an important role in facilitating stakeholder interactions. At the farm level, they coordinated discussions with district farmers, in which the RRTs sought to better understand farmers' views on current climate variability and future climate agricultural impacts. At the institute level, multi-disciplinary meetings with research scientists were held, which focused on understanding the priority climate risks raised by the farmers and devising tailored adaptation strategies. At the district level, stakeholder workshops were conducted, in which representatives of district agricultural development agencies, universities, progressive farmers, and researchers of organizations participated.

Through these discussions, it was generally found that stakeholders were interested in testing the efficacy of various technologies that can help farmers to adapt to the extreme weather events, and they expressed an interest in quantifying and anticipating changes to climate and monsoonal variability. The CT found that a top stakeholder priority is improving the reliability of climate forecasting, as this would aid farmers directly in managing their farm activities. More "near-term" time-scales of prediction, from the present to 2030, are also a priority for state- and federal-level stakeholders in order to implement and assess the efficacy of various agroeconomic policies that aid in adaptation and buffer against monsoon and climate variability.

Current AgMIP assessments have focused on the "mid-century" time-frame (2040–2069) because it was an intermediate time-frame closer to stakeholder decisions, but also late enough that the climate change signal begins to emerge from climatic variability. However, it is within the scope of near-future AgMIP activities to evaluate the impacts of climate change on regional agriculture and rural livelihood in the near-term, mid-century, and end-of-century time-frames to facilitate a range of decision-making, from short-lived subsidies and agroeconomic policies to long-term infrastructure projects, which are further detailed in each RRT's RAPs (Rosenzweig *et al.*, 2013).

Future Directions

Extended monsoon scenarios

The South Asian regional climate is dominated by a monsoonal regime, which is characterized as a fully coupled sea-land-atmosphere system, which is also subject to orographic influences (Turner and Annamalai, 2012). As such, there are many complex processes, from poleward moisture transport to low-pressure centers that traverse the region along the IGB and incite monsoonal rainfall, and the region is subject to a large amount of intraseasonal and interannual rainfall variability. Thus far, the AgMIP approach has utilized a "delta" method of imposing monthly mean climate changes (as projected by global climate models) on important agroclimate variables in a 30-year 1980–2010 climate/weather series for each modeled location. This important method aids researchers in understanding and anticipating how the mean climate will change in future periods from baseline conditions.

In continuing phases of AgMIP, the RRTs, with the help of the AgMIP leadership, will further develop tailored South Asian future climate scenarios to incorporate potential changes not just to the mean monsoon, but also in intraseasonal and interannual monsoon variability. This will entail evaluating changes to active and break periods within the monsoon to evaluate both the amount and frequency of rainfall during the growing season. Other parameters to evaluate are the monsoon onset period, withdrawal period, frequency and strength of monsoon depressions, and future influences of influential modes of climate variability, like ENSO, Indian Ocean modes of variability, and the anthropogenic warming of the Indian Ocean surface (Gadgil and Rupa Kumar, 2006; Turner and Annamalai, 2012, and references therein).

More work is needed to evaluate important agroclimatic variables in correlating with crop yields over the baseline period, with the goal of identifying parameters that can aid in future crop response to climate change. Identifying trends in the baseline monsoon circulation also proves challenging as the evaluation of different

time-periods/decades, and evaluations of different monsoon metrics, yields much uncertainty in establishing an overall response to 20th century forcings (Turner and Annamalai, 2012). A baseline agroclimatic analysis is currently being undertaken by several of the South Asian RRTs to better understand and bracket uncertainty in climate crop response.

Data management and additional regional representation

The AgMIP RRTs are generating a wealth of climate scenario information and crop and agroeconomic model results that can greatly inform regional adaptation decision-making, and agricultural and resource policy. One of the major hurdles in utilizing scientific information in policymaking is the organization, comprehensibility, and accessibility of that information. AgMIP is currently working on building a comprehensive, searchable database that contains all results from both the South Asian and Sub-Saharan African RRTs. Such a database will facilitate easy access and interpretation of the RRT's findings for particular districts and across the South Asian region, and can help to inform a wide range of agricultural development policies into the future.

Furthermore, the regional distribution of not just the modeled results, but also the AgMIP methodology, may encourage additional participation from South Asian districts and subregions that require more representation, such those from Nepal, Bangladesh, central India, and south Pakistan. Regions that display highly varying topography or large geographic gradients in temperature and rainfall (such as Sri Lanka) may also require additional sites to understand the contribution of these varying environments to spatial yield and production distributions better.

Capacity building

The continuation of AgMIP activities in South Asia will be benefited by more extensive and intensive training sessions in the areas of climate, crop, and economic modeling. The CT has contributed to the organization of "training the trainer" activities led by AgMIP in its initial phase to build capacity for the regional integrated assessments (see also Part 2, Chapter 13 in this volume). As South Asia moves to expand these assessments and methodologies, more in-region trainers will be required to help additional teams to build their modeling and analysis capacities.

Likewise, the CT envisions a number of similar training activities for those scientists that have preliminary familiarity with the tools, conducted through major coordinating institutions in each of the subregions (including ICRISAT). Such training courses would provide a certificate of completion, and allow each subregion to access analysis aid and expertise easily through their representative trainers. These

trainers would also be able to travel to various South Asian subregions to educate participants in best practices for implementing AgMIP methodologies (as per the AgMIP Protocols). These trainers will also be in a prime position to build upon and improve the AgMIP Protocols, tailoring them for unique conditions in each South Asian subregion.

The CT encourages broader consideration of student scholarship programs as a means for advancing capacity in each of the AgMIP South Asian subregions. The involvement of students in the AgMIP research process helps meet the demand for researchers who are able to contribute to integrated assessments. The CT supported undergraduate and graduate students to work alongside AgMIP researchers, in South India and Sri Lanka (Vellingiri and Zubair, 2013).

Conclusions

Agricultural production across South Asia is subject to much variability, due to natural climate fluctuations, socio-economic policies, and global shocks, and is also potentially at risk under future climate change conditions. Furthermore, a significant portion of agricultural productivity relies on natural resources, such as groundwater stores, that are fast becoming over-exploited in critical subregions (Rodell *et al.*, 2009).

AgMIP has mobilized interdisciplinary scientists across South Asia to participate in a coordinated investigation of the impact of climate change on food security (Rosenzweig *et al.*, 2013). The CT has helped scientists from highly varied and disparate subregions across South Asia, representing Bangladesh, India, Nepal, Pakistan, and Sri Lanka convene, learn new methodologies, and engage with their decision-making communities in the process of undertaking integrated assessments. The regionally tailored RAPs, which have been developed in conjunction with representative stakeholders, demonstrate the future trajectories of agricultural development and global drivers of change that are being anticipated and considered for planning and policy. The results, presented in chapters of this volume, serve as a comprehensive investigation of the important drivers of change in agricultural productivity across select districts in these countries, and they also provide a first assessment of some of the uncertainties that must be examined in order to interpret and utilize these results accurately in policy applications.

References

Aggarwal, P. K., Banerjee, B., Daryaei, M. G., Bhatia, A., Bala, A., Rani, S., Chander, S., Pathak, H., and Kalra, N. (2006). InfoCrop: A dynamic simulation model for the assessment of crop yields,

losses due to pests, and environmental impact of agro-ecosystems in tropical environments. II. Performance of the model, *Agric. Syst.*, **89**, 47–67.

Antle, J. M. (2011). Parsimonious multidimensional impact assessment, *Am. J. Agric. Econ.*, **93**, 1292–1311.

Franken, K. (2012). Irrigation in Southern and Eastern Asia in figures, AQUASTAT Survey — 2011, Rome, FAO.

Gadgil, S. and Rupa Kumar, K. (2006). The Asian Monsoon — agriculture and economy, in Wang, B. (ed.), *The Asian Monsoon*, Praxis Springer, Berlin and Heidelberg, pp. 651–683.

Grassini, P., Eskridge, K. M., and Cassman, K. G. (2013). Distinguishing between yield advances and yield plateaus in historical crop production trends, *Nature Communications*, **4**, 2918.

Government of Pakistan (2011). *Agricultural statistics of Pakistan*, *2010–11*, Government of Pakistan, Statistics Division, Pakistan Bureau of Statistics, Islamabad.

Government of Pakistan (2012). *Annual Plan 2012–13*, Government of Pakistan, Planning Commission, Planning and Development Division, Islamabad.

Hazel, P. B. R. (2008). *An assessment of the impact of agricultural research in South Asia since the Green Revolution*, Science Council Secretariat, Rome, Italy. Available at: http://www.fao.org/docrep/011/i0279e/i0279e00.HTM. Accessed on 23 April 2013.

Hoogenboom, G., Jones J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi., R., Gijsman, A. J., Tsuji, G. Y., and Koo, J. (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). DSSAT Cropping System Model, *Eur. J. Agron.*, **18**, 235–265.

Kahlown, A., and Majeed, A. (2002). Water resources situation in Pakistan: Challenges and future strategies, *J. Sci. Vision*, **7**(3&4), 33–45.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**, 267–288.

Kirtman, B., Power, S. B., Adedoyin, J. A., Boer, G. J., Bojariu, R., Camilloni, I., Doblas-Reyes, F. J., Fiore, A. M., Kimoto, M., Meehl, G. A., Prather, M., Sarr, A., Schär, C., Sutton, R., van Oldenborgh, G. J., Vecchi, G., and Wang, H. J. (2013). "Near-term Climate Change: Projections and Predictability", in Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Knox, J., Hess, T., Daccache, A., and Wheeler, T. (2012). Climate change impacts on crop productivity in Africa and South Asia, *Environ. Res. Lett.*, **7**, 034032.

Mall, R. K., Singh, R., Gupta, A., Srinivasan, G., and Rathore, L. S. (2006). Impact of climate change on Indian agriculture: A review, *Clim. Change*, **78**, 445–478.

Morton, J. F. (2007) The impact of climate change on smallholder and subsistence agriculture, *Proc. Natl. Acad. Sci.*, **104**(50) 19680–19685.

Ringler, C. and Anwar, A. (2013). Water for food security: Challenges for Pakistan, *Water Int.*, **38**(5), 505–514.

Rodell, M., Velicogna, I., and Famiglietti, J. S. (2009). Satellite-based estimates of groundwater depletion in India, *Nature*, **460**, 999–1002.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Forest Agric. Meteorol.*, **170**, 166–182.

Ruane, A. C., Major, D. C., Yu, W. H., Alam, M., Hussain, S. G., Khan, A. S., Hassan, A., Al Hossain, B. M. T., Goldberg, R., Horton, R. M., and Rosenzweig, C. (2013). Multi-factor impact analysis of agricultural production in Bangladesh with climate change, *Global Environ. Change A*, **23**, 336–350.

Turner A. G., and Annamalai, H. (2012). Climate change and the South Asian summer monsoon, *Nat. Clim. Change*, **2**, 587–595.

Vellingiri, G. and Zubair, L. (2013). Personal communication.

World Bank Group (2011). *Agriculture in South Asia: An Overview, 2014*. Available at: http://go.worldbank.org/1E8JVGXF30. Accessed on 24 April 2014.

Yahiya, Z., Adhikari, S., Weerasekara, M., and Zubair, L. (2011). *The impacts of El Nino Southern Oscillation (ENSO) events on rice production, area and yield in Sri Lanka*, FAO/SEARCA Project, FECT Technical Report 2010-01, Foundation for Environment, Climate and Technology, Digana Village, October, 2011.

Zubair, L. (2002). El-Nino-Southern Oscillation influences on rice production in Sri Lanka, *Int. J. Climatol.*, **22**(2), 249–260.

Zubair, L. (2005). Modernization of Sri Lanka's traditional irrigation system and sustainability, *Sci. Technol. Soc.*, **10**(20), 161–195.

This page intentionally left blank

Chapter 7

Impact of Climate Change on the Rice–Wheat Cropping System of Pakistan

Ashfaq Ahmad[1], Muhammad Ashfaq[2], Ghulam Rasul[3], Syed Aftab Wajid[1], Tasneem Khaliq[1], Fahd Rasul[1], Umer Saeed[1], Muhammad Habib ur Rahman[1], Jamshad Hussain[1], Irfan Ahmad Baig[4], Syed Asif Ali Naqvi[2], Syed Ahsan Ali Bokhari[3], Shakeel Ahmad[5], Wajid Naseem[6], Gerrit Hoogenboom[7], and Roberto O. Valdivia[8]

[1]*University of Agriculture, Faisalabad, Pakistan*

[2]*University of Agriculture, Faisalabad, Pakistan*

[3]*Pakistan Meteorological Department, Islamabad, Pakistan*

[4]*PMAS-Arid Agriculture University Rawalpindi, Pakistan*

[5]*Bahauddin Zakariya University, Multan, Pakistan*

[6]*COMSATS Institute of Information Technology, Vehari, Pakistan*

[7]*Washington State University, Pullman, WA, USA*

[8]*Oregon State University, Corvallis, OR, USA*

Introduction

In terms of area, Pakistan is the second largest country in South Asia and 36th largest in the world. The total geographical area of Pakistan is 79.6 million ha, of which 22 million ha are used for crop production. Most of this cultivated land is irrigated, which encompasses about 19 million ha. The majority of farmers have small land holdings; about 86% of the farms have less than 5 ha and only 5% of the farms are greater than 10 ha (Government of Pakistan, 2010). Punjab is the largest province of Pakistan both with respect to population and agricultural production. Historically the name "Punjab" is derived from two words of a local language, namely "Punj" meaning "five" and "Ab" meaning "water". Punjab encompasses five rivers, and, as a result, it has a well-developed canal system for irrigation.

There are two cropping seasons in Pakistan, Rabi and Kharif. Rabi crops are grown normally from November to April and Kharif crops are grown from May to October. These two seasons determine the agricultural economy of Pakistan. During the Rabi season wheat is dominant; during the growing season 2013–2014, it was

Table 1. Statistics of rice and wheat in Pakistan (2008–2013).

	Rice				Wheat			
	Area		Production		Area		Production	
Year	000 ha	% Change	000 tonne	% Change	000 ha	% Change	000 tonne	% Change
2008–09	2963	—	6952	—	9046	—	24033	—
2009–10	2883	−2.7	6883	−1.0	9132	1.0	23311	−3.0
2010–11	2365	−18.0	4823	−29.9	8901	−2.5	25214	8.2
2011–12	2571	8.7	6160	27.7	8650	−2.8	23473	−6.9
2012–13	2311	−10.1	5541	−10.0	8693	0.5	24231	3.2

(Government of Pakistan, 2013)

cultivated on 9.04 million ha in 2013–2014 with total production of 25.3 million tonnes. During the Kharif season rice is also an important crop; it was cultivated on 2.79 million ha in 2013–2014 with a production of 6.8 million tonnes. Sustainable production of wheat and rice is crucial for food security in Pakistan as wheat is the staple food of the people and it accounts for almost 10.3% of the total value added in agriculture. Rice is the second major source of food after wheat and accounts for 3.1% of the total value added in agriculture. Historic data (Table 1) show that the area under cultivation and production of rice and wheat was inconsistent. This inconsistency was because of water availability, shift in the monsoon patterns, and government policies for support prices of crops and subsidies for inputs (Government of Pakistan, 2014).

Climate of Pakistan

Pakistan is located on a large landmass north of the tropic of cancer between the latitude 23° to 38°N and longitude of 60°to 80°E. The climate is defined as continental characterized by extreme variation in temperature, both seasonally and daily. Pakistan is also noted for its cold winters and hot summers. Two thirds of its arable land ranges from semi-arid to arid climatic conditions, while a small zone of northeast Punjab adjoining Kashmir experiences subhumid to humid conditions. The study region lies in the semi-arid to subhumid agroclimatic zone, based on moisture index (MI) (Chaudhry and Rasul, 2004), where the maximum summer monsoon occurs during July and August. The monsoon season from July to September is generally associated with the monsoon depressions that are formed over the Bay of Bengal. They reach Pakistan via India due to their westward motion, depending upon their strength. Another cause of summer precipitation is the southwesterly

(a) Annual Rainfall (mm) Normal (1981-2010)

(b) Annual Mean Temperature (°C) Normal (1981-2010)

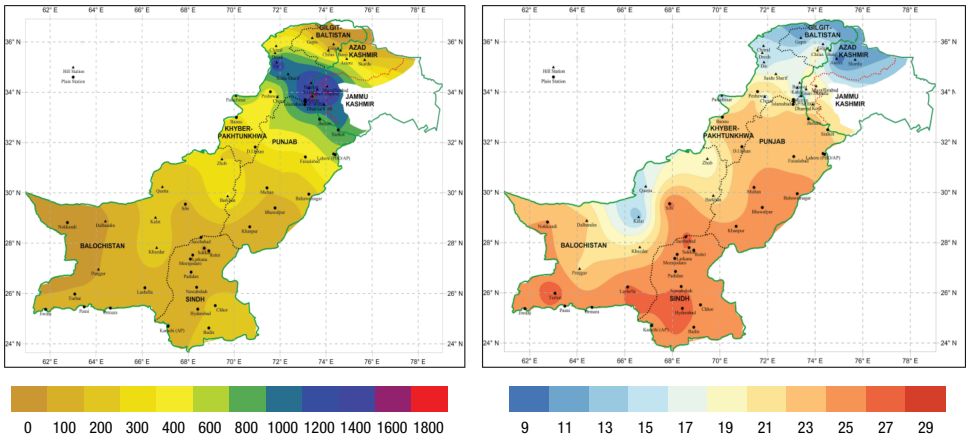


Fig. 1. Climate of Pakistan 1981–2010 (a) annual rainfall (mm) (b) annual mean temperature (°C).

flow of moisture from the Arabian Sea which is activated with the persistence of a mesoscale low pressure over land. Both phenomena of monsoon and moisture from the Arabian Sea reinforce the precipitation process and produce high-intensity rainfall. The rice crop mainly depends upon rainfall during monsoon season (July to September).

Winter precipitation is produced by western disturbances which are troughs of westerly waves passing across the mid-latitudes. Due to such weather systems, the northern half of Pakistan receives a reasonable amount of precipitation in the form of rainfall as well as snowfall over the north and west mountainous regions (Chaudhary and Rasul, 2004). Chaudhary and Rasul (2004) characterized Pakistan's arable area into different agroclimatic zones on both an annual and seasonal basis using a MI. Water from snow and glacier melt is important during May and June when rice is sown and coincides with the extremely hot and dry pre-monsoon season. Winter rains are very important for wheat in the rainfed areas, especially at crown root initiation and reproductive stages. The area used in this study was mostly irrigated during Rabi season (Ghazala *et al.*, 2009). In the rice–wheat cropping system, wheat is generally sown in December after the rice harvest and moisture deficit has never been a problem. However, the heavy rain just after sowing hampers the emergence of seedlings out of the crusted soil. As the wheat crop is mainly irrigated, air temperature, relative humidity, and solar radiation play a more important role than rainfall for crop growth and development as well as the incidence of pests and diseases during the growing season (Rasul *et al.*, 2012).

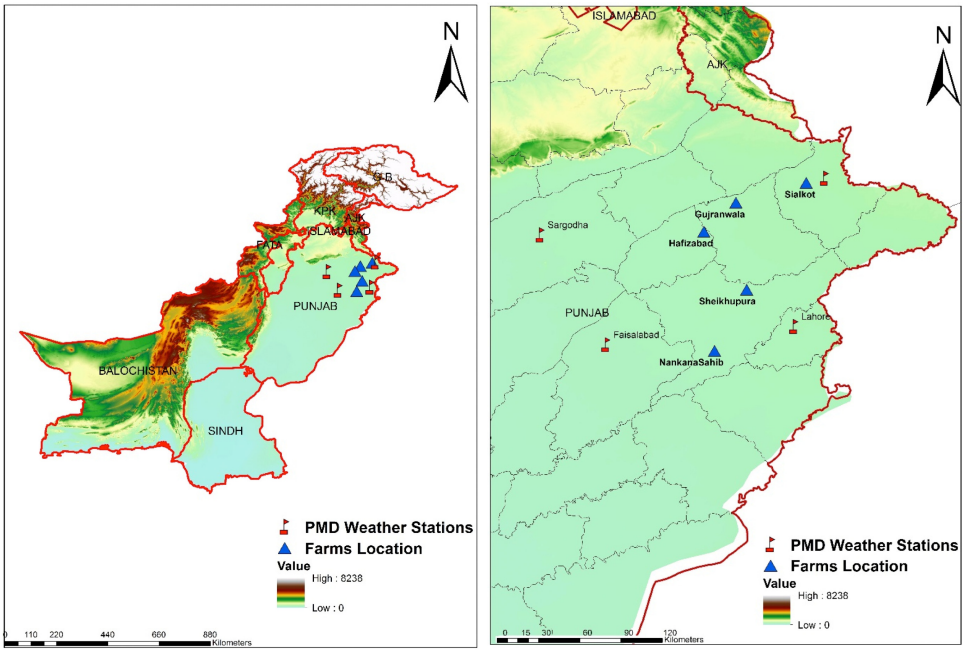


Fig. 2. Location and elevation of integrated assessment study region.

Cropping Systems in Pakistan

Wheat, rice, sugarcane, maize, and cotton are the most important agricultural crops grown in Pakistan. As a result, Pakistan has three main cropping systems, namely rice–wheat, mixed wheat, and cotton–wheat on the basis of Kharif crops. These cropping systems are mainly found in the subhumid area in the northern part of the country, the semi-arid area in the central part of the country, and the arid area in southern part of the country, with different systems for the different regions of Punjab (Fig. 1). Small to medium land holdings and a very low percentage of tenancy is the character of the rice–wheat zone. The number of very small farmers (1.5 ha) and very large farmers (>20 ha) are relatively small, although several very large farmers operate over 100 ha, especially in Gujranwala District. The rice–wheat cropping system covers 1.1 million ha, centered in the districts of Sialkot, Gujranwala, Sheikhupura, Nankansahib, and Hafizabad (Fig. 2).

Issues and Challenges

A change in local weather conditions due to climate change threatens the productivity of the agricultural sector, which makes it vulnerable both biophysically and

economically. Some regions are likely to benefit from climate change while other regions could be adversely affected. An increase in temperature, changes in rainfall trends and extreme weather events are raising concerns about the prospective impact on water, food, and energy.

There are five main risks related to climate change in Pakistan: A rise in sea level, glacial retreats, more frequent and heavier floods, higher temperatures, and an increase in the frequency of droughts. Such risks raise major challenges for current and future decision-making and have a resounding impact on agriculture, water resources, urban–rural management, and the overall economy. Since 2001, Pakistan has repeatedly borne witness to history's worst disasters, and indeed Pakistan ranked 12th in the 2014 Global Climate Risk Index and was among the three worst affected countries worldwide over three consecutive years in terms of climate-related calamities (Kreft and Eckstein, 2013). Pakistan suffered from severe flooding in both 2010 and 2011 and was struck again by a rough monsoon season in 2012, which killed over 650 people. Floods in 2010 were the worst in its history, causing nearly 3000 deaths and affecting 20 million people (WMO-No.1119). The 2012 monsoon seasonal rainfall averaged over Pakistan was 257%, Sindh 1100%, Punjab 405%, and Baluchistan 338%, compared to the long-term average total due to unusually intense rainfall during September. The 2012 floods affected around three million people in Pakistan, damaged thousands of hectares of agricultural crops, and claimed approximately 450 lives (Blunden and Arndt, 2012).

Agriculture is always vulnerable to climate change, and this is especially so in Pakistan because of its arid and semi-arid ecosystems (Janjua *et al.*, 2010) (an increase in temperature would affect arid and semi-arid areas more than humid regions). Although changes in precipitation are variable, there are indications of an overall increase in precipitation over South Asia during the coming decades. Heavy rainfall events are expected to increase during the rainy season, increasing the chances of floods, while the dry seasons are expected to get drier. According to the IPCC (2002), precipitation increased an average 40% in the southeast, 20% in the north and 10% in central part of Pakistan during the 20th century (Gitay *et al.*, 2002).

Developing economies are often more climate-sensitive because they rely on labor-intensive technologies, whereas developed economies can cope with climate extremes as technology is more readily available and adoption rates are higher (Kurukulasuriya *et al.*, 2006; Mendelsohn *et al.*, 2001; Seo and Mendelsohn, 2008). Productivity in Pakistan is affected by a number of climatic variables including rainfall patterns, rising temperature, and elevated CO_2. In 1949–1950, the agricultural sector contributed 53% to Pakistan's GDP, which dropped to 31% during 1980–1981, and to 21.4% during 2012–2013. The floods of 2010 affected 20% of the land area and the overall production loss of sugar cane, paddy, and cotton was

estimated at 13.3 million tones. Two million ha of standing crops were either lost or damaged. Between 60% and 88% of the farming households reported losses of more than 50% of their major crops, including rice, vegetables, cotton, sugar, and fodder (GOP, 2011). Agricultural growth suffered a serious setback during 2000–2001 as a result of drought. The major crops registered decreased growth of almost 10%, while overall decrease in growth was 2.6%.

The extent of hazards due to climate change in Pakistan is large and could be more challenging in the future. It is, therefore, important to quantify the impact of climate change on all vulnerable systems and particularly on agriculture; keeping in view the magnitude of the problem. The team engaged with the Agricultural Model Intercomparison and Improvement Project (AgMIP) has started to quantify climate change effects on the rice–wheat cropping system at the farm level through the use of climate, crop, and economic models. The overall goal is to develop adaptation strategies to counter the potential negative effects of climate change, to improve the livelihood of small-holder farmers in the project area, to disseminate this information to farmers, policymakers, and extension workers, and to strengthen partnerships among the relevant stakeholders.

Rice–Wheat Cropping System

The rice–wheat cropping system is centered in the districts of Sialkot, Gujranwala, Sheikhupura, Nankansahib, and Hafizabad and occupies 1.1 million ha of farming land. Most of the fields are sown in an annual rice–wheat cropping pattern and about 72% of wheat is sown after rice. The rice–wheat system has special problems and conflicts in crop management for the two crops. Rice requires puddled compacted soils to hold standing water during the growing season. Hence for rice cultivation, the puddling operation to form a hard pan is important for water retention. It decreases soil porosity and markedly alters the porosity distribution by mixing soil separates to enhance water retention of soil. Wheat grows best in well-drained soils that allow deep penetration of the root system. However, unless this hard pan is broken, wheat could suffer from problems of water-logging. Another issue in rice–wheat management is caused by the dominance of late-maturing rice varieties that allows little time for land preparation for wheat that ultimately delays the wheat cultivation.

Issues of water scarcity and management figure highly in this system. Many farmers list water stress as an issue. Labor shortages during the major cultural operations, especially at planting, harvesting, and threshing, are also increasing. Nutrient imbalance and mining by rice and wheat have led to problems in some areas. Nitrogen and phosphorus are two of the most important macro-nutrients that have become limiting in the rice–wheat system. Zinc, boron, and manganese are micro-nutrient problems in some areas. Declines in soil organic matter could be due to problems with the rice–wheat system.

The sowing time for wheat in this region is from 20 November to the end of December. The common seeding rate is 100–125 kg ha^{-1} and the seed bed is prepared by two to three cultivations followed by two plankings. Some farmers prepare the seed bed by using residual moisture after harvesting rice crop to save time and avoid delay in wheat sowing. The sowing method that is normally practiced by farmers is a broadcast; the fertilizer level that is commonly used in the area is 135:61:0 kg ha^{-1} N:P:K. Farmers usually apply four to five irrigations at critical growth stages (crown root initiation, stem elongation, booting and heading, and grain development) to wheat depending on weather conditions. It is generally harvested by mid-April (Table 2). However, progressive farmers use a drill for sowing and a combine harvester for harvesting wheat. Average yield levels range from 3000–3500 kg ha^{-1}. Common wheat varieties in the region include Sahar-2006, Faisalabad-2008, and Lasani-2008.

The rice nursery is generally sown from 20 May to 20 June and 30- to 40-day-old seedlings are used for transplanting. Approximately 5–7 kg of seed is used in the nursery for transplanting on an area of one ha. Land is prepared with two cultivations after the harvesting of wheat two months prior to transplanting. At the time of transplanting, four to five cultivations are done followed by planking in standing water to puddle the soil and creation of the hardpan to keep water standing in the crop and create anaerobic conditions. Generally no fertilizer is applied at the time of land preparation, but is applied after one week of transplanting. The average fertilizer levels that are used are 120:100:0 kg ha^{-1} N:P:K. The number of irrigations ranges from 35–40. Rice is harvested in October to November (Table 2), with an average yield of 4000 kg ha^{-1}. The common varieties that are sown in the region include Super Basmati, Basmati-385, and Basmati-2,000.

Methodology

Socio-economic data

Survey data for rice, wheat, and livestock for the rice–wheat cropping zone of Punjab were collected for this study. An extensive farm survey for 155 farms from the selected five districts was conducted. Because the population was heterogeneous in nature, a stratified random sampling technique was used. The districts of this study included Sheikhupura, Nankana Sahib, Hafizabad, Gujranwala, and Sialkot. Two villages were taken randomly from each district. Each district was taken as a separate stratum, because of its own climatology and topography. From each stratum at least 30 respondents and at least 15 farms from each village were chosen randomly so that the selected sample could be a true representation of the farming population. Missing values, like the management practices (sowing and harvesting

Table 2. Crop management practices data of rice and wheat used for crop modeling analysis for the rice–wheat cropping system of Punjab.

		Rice							Wheat						
Serial No.	Stratum	PD	HD	N	P	T (no)	Irri. (No)	Irri. (mm)	PD	HD	N	P	T (no)	Irri. (No)	Irri. (mm)
1	Sheikhupura	20th	October	109	29	4	37	1,586	20th	March	132	63	4	4	402
2	Nankana Sahib	May	to	120	18	4	36	1,721	November	to	139	64	4	4	397
3	Hafizabad	to End	November	111	—	4	36	1,636	to	April	142	57	4	4	390
4	Gujranwala	of June		123	34	4	36	1,617	end		125	60	4	3	287
5	Sialkot			103	22	4	36	1,584	December		137	60	4	4	401

PD: Planting date, HD: Harvesting date, N: Nitrogen (kg ha^{-1}), P: Phosphorus (kg ha^{-1}),
T: Number of tillage applications, Irri.: Irrigations.

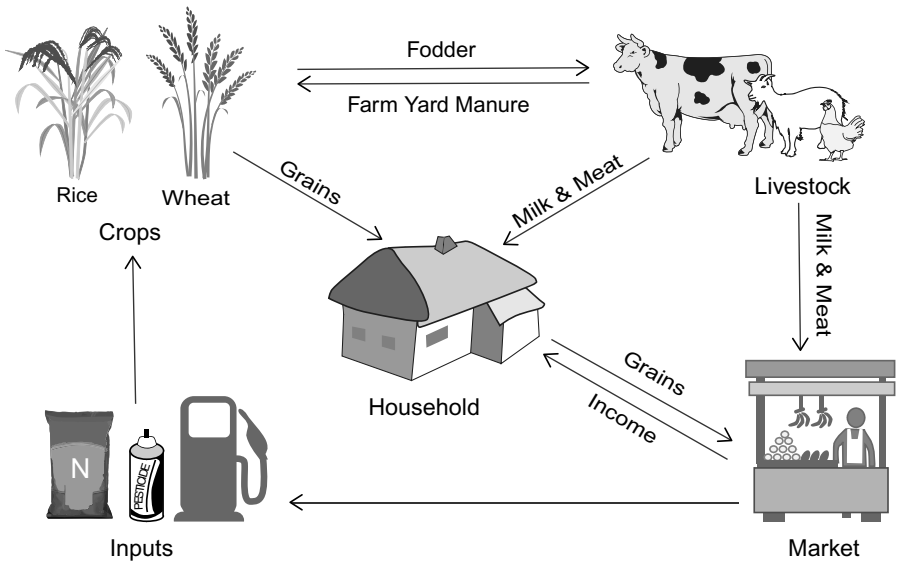


Fig. 3. Rice–wheat farming system of Pakistan.

dates, non-farm income, and other crops, etc.) were supplemented from the same farmers later on through personal contact. The economic analysis was conducted on a per farm basis. The farming system diagram for the region surveyed is shown in Fig. 3.

Climate

The past climate of the study region was analyzed by using the available weather station data. The climate change projections for the region were generated by using output of five general circulation models (GCMs) of the latest CMIP5 (Coupled Model Intercomparison Project) family. Based on meteorological data of five surrounding locations in the area of study, the gradients of precipitation and temperature were developed as the terrain and ecological features were not much different (Fig. 2). The delta method was applied for projecting the future climate under the relatively high-emission climate change scenario, i.e., RCP (representative concentration pathway) 8.5.

Observed trends in temperature and precipitation

The annual rainfall (1981–2010) in the study region varied from 400 to 1000 mm with most of the rain in the Sialkot district falling during summer monsoon (Fig. 1). The observed meteorological data for Sialkot and Sheikhupura districts were analyzed

for annual daily mean temperature (°C) and annual total precipitation (mm) as well as decadal averages for the period from 1931–2010. For Sialkot, an increase in temperature of 1.91°C was recorded from 1931–1947 and after that a decrease was observed until 2000 with a total decline of 2.13°C. The most recent decade 2001–2010 was the warmest among the past seven decades. For the Sheikhupura district during the first four decades starting from 1931, the mean temperature varied between 24°C and 24.5°C. After 1970, there was a rising trend until 2010 with an increase of 1°C as compared to mean temperature during 1960s and 1970s. For rainfall there was a large interannual variability in both districts, with Sialkot having the highest decadal average of 1108 mm during 1991–2000. Sheikhupura received the highest decadal average rainfall of 719 mm during 1981–1990 (Fig. 4a). The

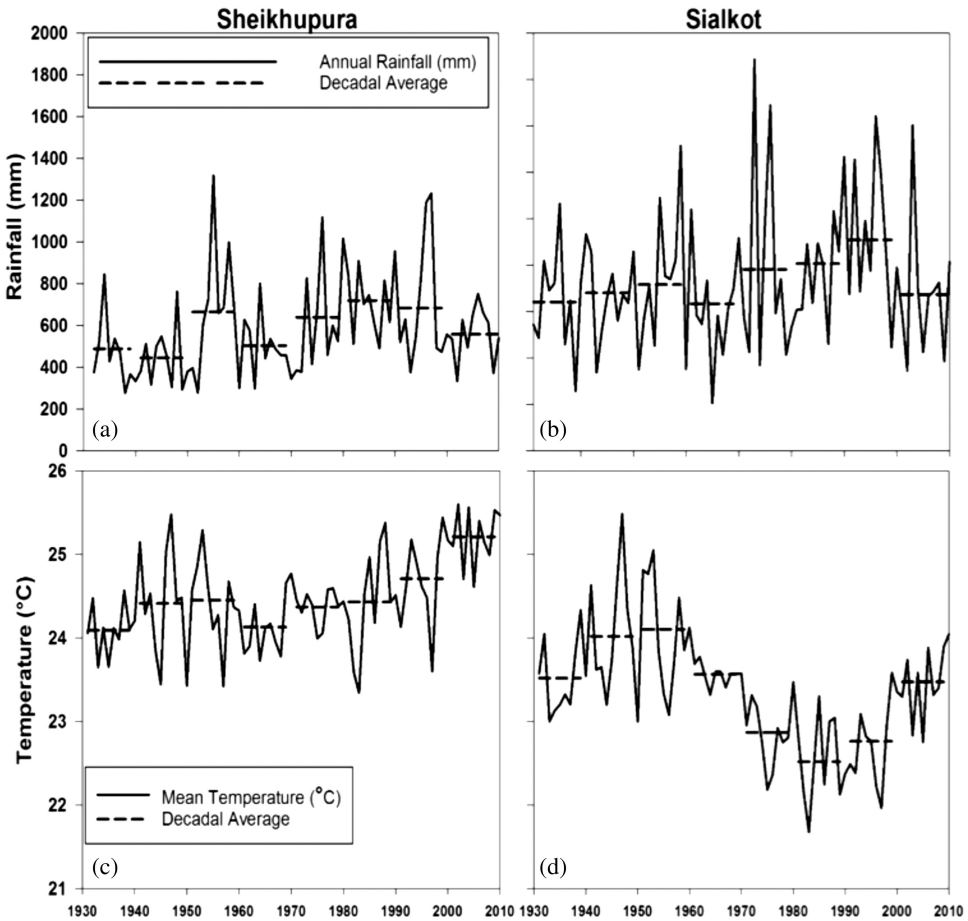


Fig. 4. Observed trends in annual mean temperature (°C) and annual precipitation (mm) and decadal average (1931-2010) for rice-wheat districts Sialkot (a & c) and Sheikhupura (b & d).

maximum annual rainfall in Sialkot was observed in 1973 with a total of 1886 mm, while Sheikhupura received its maximum rainfall in 1955 that amounted to 1317 mm. The minimum annual total for Sialkot was 368 mm in 2011, while Sheikhupura received a minimum rainfall of 277 mm in 1938.

Baseline climate data

Sialkot and Sheikhupura are the only two districts where meteorological observations were available for the complete baseline period (1981–2010). The quality of the available weather station data was checked and the datasets were converted to .AgMIP files as described in the AgMIP protocols (Rosenzweig *et al.*, 2013a). For preparation of baseline data for the rest of the three districts, background daily weather time series (1981–2010) were obtained from the global AgMERRA (Modern Era-Retrospective Analysis for Research and Applications) dataset (see Part 1, Chapter 3 in this volume). The AgMERRA time-period covers the modern era of remotely sensed data, from 1979 until present, and the special focus of the atmospheric assimilation is the hydrological cycle (Ruane *et al*., 2014).

Baseline data for the corresponding three districts (Hafizabad, Nankana Sahib, and Gujranwala) were estimated in a manner similar to the gap-filling bias adjustment of the AgMIP protocols (Rosenzweig *et al.*, 2013a). The differences in monthly climatology were calculated between the AgMERRA dataset for Hafizabad and Nankana Sahib, where distance was greater than ∼50 km from the weather station (Ruane *et al*., 2014) and the WorldClim dataset (Hijmans *et al*., 2005) for the Gujranwala, where the distance was less than ∼50 km from the weather station. For the temperature, the monthly bias was subtracted from the corresponding month's daily AgMERRA data, while for rainfall the monthly bias was multiplied by the corresponding month of the AgMERRA data. This resulted in a continuous, complete, physically consistent daily climate series for all five districts from 1981–2010.

Climate projections

Delta scenarios (Wilby *et al*., 2004) are based on historical baseline daily weather data; with each day's weather variables perturbed by using the changes in climate model outputs for future mid-century RCP8.5 (Moss *et al.*, 2010) versus those same model outputs for the historical time-period. Five CMIP5 GCMs, CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR (Taylor *et al*., 2012), were used for the generation of climate projections (Part 1, Chapter 3 in this volume). The selection criterion of these GCMs was based on several facts such as the track record of publications, better performance in monsoon regions and reputation of the model developing institute (Rosenzweig *et al*., 2014).

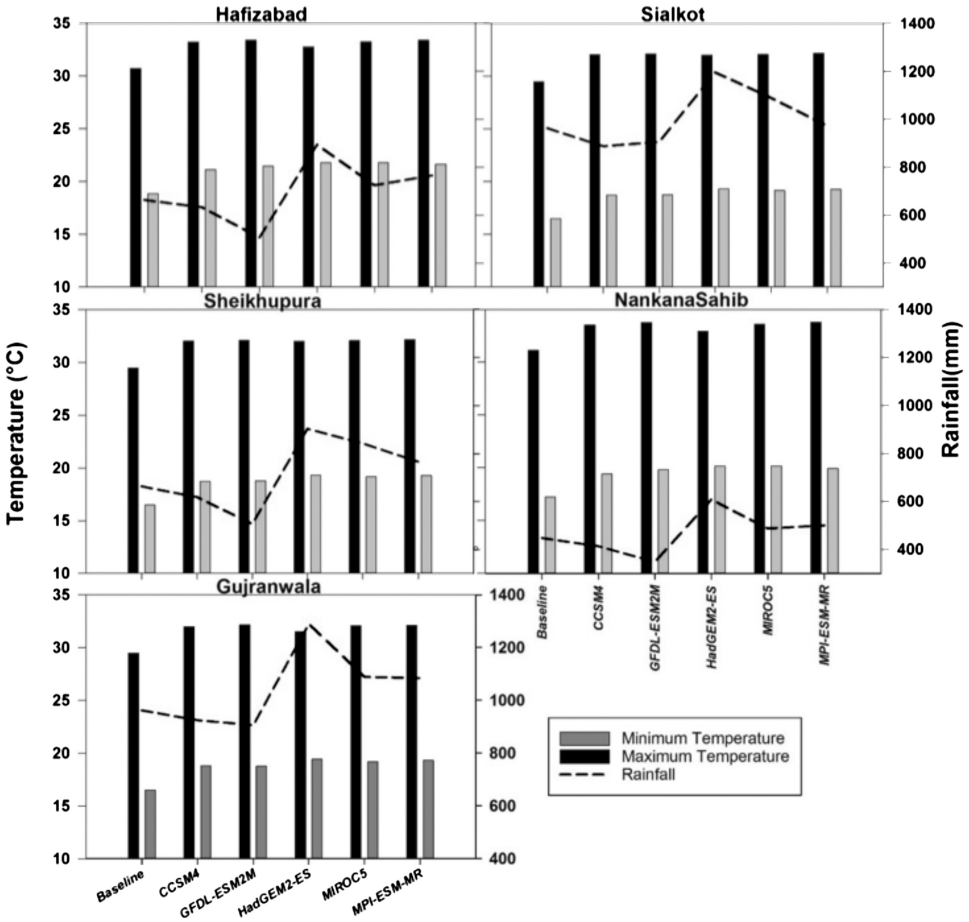


Fig. 5. Climatology (Tmax, Tmin, and precipitation) for the baseline period (1980–2010) and projections for mid-century RCP8.5 scenario for (a) Hafizabad, (b) Sialkot, (c) Sheikhupura, (d) Nankana Sahib, and (e) Gujranawala.

The baseline (1981–2010) was taken as reference for comparison to assess the change in the projected climatic parameters. The future mean, maximum, and minimum temperatures and precipitation the RCP8.5 mid-century projections for all stations are presented in Fig. 5 along with the baseline. All five selected models performed consistently to project the thermal regime for the future in terms of daily maximum and minimum mean temperatures. Figure 5 shows an increase of about 2°C in temperature during the mid-century (2040–2069) period under the RCP8.5 scenario. However, heterogeneous model output was seen in the case of precipitation projections for the selected study area. There is a remarkable difference among the output of the GCMs in the projected values of precipitation for all five districts of Punjab. The HadGEM2-ES was the wettest of all five, projecting a 200-mm increase

in precipitation on average in the area of study, while GFDL-ESM2M was the driest showing an expected decrease of about 100 mm for 2040–2069. The ensemble mean of the five GCMs shows a slight increase in annual rainfall (mm) as compared to the baseline.

In order to further examine projected climate change for the mid-century RCP8.5 scenario for the selected stations, the annual cycle of maximum temperature, minimum temperature, and precipitation was calculated for each district. There is a clear signal of warming for all five selected districts as the five CMIP5 GCMs show an increase of 2°C to 3°C as compared to the baseline. However, this increase is not uniform for all five CMIP5 GCMs. For example, CCSM4 and GFDL-ESM-2M are showing more warming for the months of April and September, respectively. There are some exceptional cases like projection of MPI-ESM-MR, in which the rainfall shows abrupt increases and decreases as compared to the normal pattern. There is mixed behavior of GCMs towards projected precipitation as compared to the baseline. Some CMIP5 GCMs (e.g., HadGEM2-ES and MIROC5) are wet while other GCMs (e.g., CCSM4 and GFDL-ESM-2M) are dry as compared to the precipitation of the baseline period.

Crop modeling

Crop models are being used to evaluate both the spatial and temporal production uncertainties due to crop management and climate scenarios (Hoogenboom, 2000). Crop models have their applications in the fields of research, decision support, education, and training (Jones *et al.*, 2003). Crop simulation models have the potential to help understand the impact of climate change, climate variability, and agronomic practices on plant growth and development as the models integrate the soil–plant–atmosphere complex. Two crop growth models were used in this study, including DSSAT and APSIM.

Decision Support System for Agrotechnology Transfer (*DSSAT*)

DSSAT is a comprehensive decision-support system (DSS) for assessing crop management options. Crop simulation models use one set of code for simulating soil water, nitrogen, carbon dynamics, crop growth and development, and yield of crops (Hoogenboom *et al.*, 2012; Jones *et al.*, 2003). The simulations are based on physiological processes that describe the response of the crop to soil and aerial environmental conditions. DSSAT has been used widely to simulate the collective effects of plant genetics, management practices, weather and soil conditions on the growth, development and yield of wheat and rice in Pakistan and other countries in

South Asia (Ahmad *et al.*, 2009; Ahmad *et al.*, 2011; Ahmad *et al.*, 2012; Ahmad and Hasanuzzaman 2012; Mall and Aggarwal, 2002; Sarkar and Kar, 2006).

The inputs that are required for model operation include management practices, environmental factors, and daily weather data. A set of cultivar-specific coefficients that characterize the cultivar being grown in terms of plant development and grain biomass; and crop management information, such as plant population, row spacing, seeding depth, and application of fertilizer and irrigation. The cropping system model (CSM) CSM-CERES-Wheat and CSM-CERES-Rice require a set of seven and eight cultivar coefficients for simulation of phenology, growth, and yield of cultivars, respectively. The cultivar coefficients were estimated through iteration approach using the sensitivity analysis option of DSSAT (Ahmad *et al.*, 2011; Ahmad *et al.*, 2012). The cultivar coefficients were determined sequentially, starting with phenological parameters, followed by the grain-filling parameters, and finally total biomass and grain yield (Hunt and Boote, 1998). The models simulate phenological development, biomass accumulation and partitioning, leaf area index, stem and leaf growth, and the water and N balance from planting until harvest at daily time steps.

Agricultural Production Systems Simulator (*APSIM*)

APSIM is a cropping system modeling framework that was developed by the Agricultural Production Systems Research Unit in Australia (Keating *et al*., 2003). It is a highly advanced simulator of agricultural systems to evaluate management options, agronomic practices for supporting on-farm decision-making, designing farming systems for production and experimental design or resource management objectives, and assessing the value of seasonal climate forecasting as well as plant, animal, soil, climate, and management interactions (Buckthought *et al.*, 2011). APSIM can estimate profitability, economic risk, yield, animal production, and effects on the environment. It can be used to analyze risk and explore alternative management options such as crop choice, planting date, and fertilizer rate, using local climate data and paddock-specific soil data. When used interactively with farmers, it can also take into account the social and/or economic values or goals that influence an individual farmer's management decisions (Gaydon *et al.*, 2012; Keating *et al.*, 2003; Stone and Heinemann, 2012).

Experimental data used for model calibration

Rice

The data on rice phenology, yield, yield components, and management practices were obtained from field trials conducted on fine aromatic rice cultivars Basmati-385, Super Basmati, and Basmati-2000 at the Agronomic Research Farm, University

of Agriculture, Faisalabad, Pakistan during the 2000, 2001, 2004, 2005, 2009, and 2010 growing seasons. In these experiments rice was transplanted and grown under flooded conditions until maturity. Different crop management practices such as transplanting date, plant population density, irrigation levels, nitrogen rates, and split application of nitrogen and varietal behavior were tested. A brief description of methodology adopted in the field experimentation is given below.

i. Experiments conducted during 2000 and 2001

Two years of field trials for assessing the effect of nitrogen management and planting density on growth, development and yield of rice were conducted at the Agronomic Research Area (Ahmad *et al*., 2009). The performance of an aromatic fine rice cultivar Basmati-385 under an irrigated semi-arid environment was evaluated. Three planting densities, i.e., one, two, and three seedlings per hill, respectively, were randomized in the main plots and five nitrogen application rates, 0, 50, 100, 150, and 200 kg N ha^{-1} were randomized in subplots. The models were calibrated with the best treatment which was 200 kg N ha^{-1}. A more detailed description can be found in Ahmad *et al.* (2012).

ii. Experiments conducted during 2009–2010

Data from a two-year field study data were used to calibrate the cultivar coefficients, including Super Basmati, Basmati-385, and Basmati-2000. The study was conducted at the same experimental farm as previously described during the rice-growing season of 2009 and 2010. The experiments were laid out in randomized complete block design (RCBD) with split arrangements that had three replications. The treatments consisted of three planting dates, i.e., 1, 15, and 30July, and three cultivars, i.e., Super Basmati, Basmati-385, and Basmati-2000. The model was calibrated with a planting date of 1 July.

Wheat

Two years of field trials for the assessment of nitrogen management on growth, development, and yield of wheat were conducted at the agronomic research area, University of Agriculture, Faisalabad, Pakistan, to evaluate the performance of various genotypes under irrigated conditions in a semi-arid environment. An RCBD with split arrangement was employed with three replications. In both years the experiment was planted in the same field that had a silt–clay–loam soil named as Lyallpur series. Four nitrogen rates, including 0, 55, 110 (standard), and 220 kg ha^{-1} were randomized in the main plot and ten wheat varieties were located in the subplot. Wheat was planted during the second week of November 2008–2009 and

2009–2010, with the help of a single-row hand-drill, keeping a row-to-row distance of 30 cm, and using a seeding rate of 100 kg ha^{-1}. Phosphorus and potassium were applied in all plots at the rate of 85 and 60 kg ha^{-1}, respectively, in the form of triple super phosphate and sulphate of potash, and nitrogen in the form of urea at the time of seed-bed preparation. All cultural practices such as weeding, interculturing practices, irrigation, etc., were kept uniform for all the experimental treatments. Two split doses of nitrogen fertilizer were applied: The first dose of half the nitrogen fertilizer was applied at the time of first irrigation after 35 days of sowing and the second split of half of nitrogen fertilizer at the time of second irrigation 25 days after the first irrigation in both years.

Data on phenology and development were recorded during the vegetative and reproductive phases in both years. Anthesis was recorded when ears were visible outside the leaf sheath on 50% of the plants in each plot. Physiological maturity was determined by regular sampling of grains from primary tillers. For the growth analysis, seven harvests were obtained at 14-day intervals during each growing season. Plants from a one-meter row were harvested from each experimental unit randomly. The plants were separated into individual components like leaves, stem, and grains. A subsample of 100–200 g of green leaves and branches were oven-dried to a constant weight at 60°C to determine the dry weight. A subsample of 50–100 g of green leaves was taken and the leaf area was measured with an electronic leaf area meter (Licor, model 3100). The leaf area index (LAI) was calculated as the ratio of total leaf area to occupied surface area. At maturity, half the plot was harvested manually to record the final biomass, grain yield, and yield components.

Statistical analysis

All observed and simulated results of calibration and evaluation were compared to assess the accuracy of models using statistical analyses, including root-mean-square error (RMSE), d-stat, coefficient of determination (R^2), percentage difference (PD), and mean percentage difference (MPD).

Calibration and evaluation results

DSSAT–Rice

Data from two field experiments were used to calibrate CSM-CERES-Rice. Basmati-385 cultivar was used in the first field experiment to calibrate the model with a treatment of two seedlings per hill and nitrogen at 200 kg ha^{-1}, because this treatment had the highest yield in the field. In the second field trial, the model was calibrated for cultivars Super Basmati and Basmati-2000 with a transplanting date of 1 July. During calibration, the model predicted the number of days to anthesis with 0%, 0%, and 1.58% PD for Basmati-385, Super Basmati, and Basmati-2000,

respectively. For grain yield, the PDs were 1.4%, 3%, and 1.4% for Basmati-385, Super Basmati, and Basmati-2000, respectively. Corresponding results of biomass production were 2.1%, 1.6%, and 1.3%.

For model evaluation, the RMSE in Basmati-385 for grain yield ranged between 41 and 156 kg ha^{-1} during 2000 and between 154 and 461 kg ha^{-1} in 2001 with MPD of 3–6% in 2000 and 3.6–10% in 2001. The R^2 between observed and simulated grain yield was 0.99 (2000) and 0.98 (2001). The RMSE for grain yield of Super Basmati and Basmati-2000 remained 203 kg ha^{-1} in 2009 and 237 kg ha^{-1} in 2010, while for Basmati-2000, it was 194 kg ha^{-1} during 2009 and 206 kg ha^{-1} during 2010. MPD for grain yield was 4% and 6% during 2009 and 2010 for Super Basmati and 4% and 5% during 2009 and 2010 for Basmati-2000, respectively. The R^2 for the evaluation dataset was 0.98 in grain yield for both cultivars.

APSIM–Rice

APSIM–Rice was calibrated using data from the second field experiment regarding varietal response to sowing dates. During calibration, the model predicted days to anthesis with PDs of 1.6%, 0.0%, and 3.3% for cultivars Basmati-385, Super Basmati, and Basmati-2000 respectively. So far as the PDs of yield were concerned, the model predicted a yield with a PD of 2.7%, 0.45%, and 0.56% for cultivar Basmati-385, Super Basmati, and Basmati-2000, respectively. Model simulations for above-ground biomass showed PDs of 4.6%, 6%, and 4.5% for Basmati-385, Super Basmati, and Basmati-2000, respectively. The model was evaluated with the remaining experimental treatments of 2009 and evaluated with data collected in 2010. The RMSE for grain yield of Basmati-385 was 377 kg ha^{-1} (2009) and 463 kg ha^{-1} (2010). The d-stat for Basmati-385 was 0.65 for 2009 and 0.69 for 2010. In the case of Super Basmati, the MPD for grain yield was 8.9% for 2009 and 5.4% for 2010. The RMSE for grain yield of Super Basmati was 422 and 685 kg ha^{-1} for 2009 and 2010, respectively. The values of d-stat were 0.001 (2009) and 0.31 (2010). Model evaluation was good in the case of Basmati-2000 as MPDs for grain yield were 3.7% and 7.2% for 2009 and 2010, respectively. The values for RMSE were 202 kg ha^{-1} and 770 kg ha^{-1} for 2009 and 2010, respectively. The value for d-stat (0.59) for 2010 was good as compared to the evaluation d-stat (0.35) value.

DSSAT–Wheat

For the calibration of the CSM-CERES-Wheat model with experimental data, the 110 kg N ha^{-1} treatment performed well in the field during both the years, so it was used for model calibration (2008–2009), while the other treatments (0, 55, 220 N kg ha^{-1}) were used for model evaluation to judge the accuracy of model and

genetic coefficient performance. A close agreement was obtained between observed and simulated values for phenology, LAI, biomass, and grain yield for all cultivars (Fasisalabad-2008, Lasani-2008, and Sahar-2006). The values of PDs were 0.8%, 1%, and 5% for Faisalabad-2008, Lasani-2008, and Sahar-2006, respectively for the grain yield. As regards biomass, the PDs were 1.6% for Faisalabad-2008, 1.5% for Lasani-2008, and 3.3% for Sahar-2006.

For evaluation of the CSM-CERES-Wheat model, it was run with the remainder of the treatments of the experiment that were conducted in 2008–2009 and then evaluated with the data of the 2009–2010 experiment. The values of MPDs for grain yield were 3%, 4.5%, and 13% for cultivars Faisalabad-2008, Lasani-2008, and Sahar-2006, respectively, for 2008–2009. Corresponding values for MPDs for grain yield were 6%, 6.5%, and 3%. The values for RMSE of grain yield were 176 kg ha^{-1} for Faisalabad-2008, 204 kg ha^{-1} for Lasani-2008, and 415 kg ha^{-1} for Sahar-2006 for 2008–2009. In 2009–2010, corresponding values of RMSE for grain yield were 282, 221, and 324 kg ha^{-1}. The index of agreement (d-statistics) was 0.99 for Faisalabad-2008, 0.98 for Lasani-2008, and 0.92 for Sahar-2006 for the year 2008–2009. For evaluation with the data of the 2009–2010 experiment, the d-statistics were 0.97 for Faisalabad-2008, 0.98 for Lasani-2008, and 0.96 for Sahar-2006.

APSIM–Wheat

The APSIM–Wheat model was calibrated for the same three wheat cultivars (Faisalabad-2008, Lasani-2008, and Sahar-2006) at the optimum nitrogen rate of 110 kg ha^{-1} during 2008–2009. Calibration performance of model for all recorded parameters was good. Statistical indices showed that there was a close agreement between observed and simulated phenology, grain yield, and biomass for all cultivars. The PDs for days to anthesis were 0.9%, 1.9%, and 1.9% for Faisalabad-2008, Lasani-2008, and Sahar-2008, respectively. PDs of maximum leaf area index (LAIX) were the highest (13%) for Sahar-2006 and the lowest (5.6%) for Lasani-2008, while for Faisalabad-2008 had a value of 10.6%. Genetic coefficients were adjusted with little difference in observed and simulated grain yield. The PDs between simulated and observed were –0.80%, –0.5%, and –3.2% for the cultivars Faisalabad-2008, Lasani-2008, and Sahar-2006, respectively. The PDs for simulated biomass of Faisalabad-2008 and Sahar-2006 were –0.04% and –6.1%, respectively, but 0.3% for Lasani-2008.

For evaluation of the APSIM model, it was run with rest of the treatments of experiment conducted in 2008–2009 and then evaluated with the data of the 2009–2010 experiment. The values for MPDs for grain yield were 14%, 13%, and 10% for cultivars Faisalabad-2008, Lasani-2008, and Sahar-2006, respectively, for 2008–2009. During 2009–2010, the values for MPDs were 1.5%, 8.4%, and 3.7% for

Faisalabad-2008, Lasani-2008, and Sahar-2006 respectively. The values for RMSE for grain yield were 609 kg ha^{-1} for Faisalabad-2008, 629 kg $ha^{-1}$for Lasani-2008, and 498 kg ha^{-1} for Sahar-2006 for the year 2008–2009. In 2009–2010, the values for RMSE for grain yield were 340 kg ha^{-1} for Faisalabad-2008, 650 kg ha^{-1} for Lasani-2008, and 581 kg ha^{-1} for Sahar-2008. So far as d-stat is concerned, it was 0.92 for Faisalabad-2008, 0.89 for Lasani-2008, and 0.94 for Sahar-2006 for 2008–2009. For evaluation with the data of 2009–2010, the values for d-stat were 0.98 for Faisalabad-2008, 0.89 for Lasani-2008, and 0.93 for Sahar-2006.

On-farm model evaluation

The household surveyed data described above were used to create crop management files for both models. The initial conditions, input levels, and soil characteristics of the field that were obtained from the surveys were used to define the input data for both models. Then the models were run with observed weather data of the cropping year, i.e., 2010.

DSSAT–Rice

The CSM-CERES-Rice model was evaluated with farmers' field data for 155 fields of rice from five districts of Punjab in the rice–wheat cropping zone. There was a good agreement between predicted and observed farmer rice yield with an RMSE of 409 kg ha^{-1}, a d-stat of 0.80, and a bias of 0.94 (Fig. 6). The CSM-CERES-Rice model simulated rice yield with percent error ranging from –17.6% to 24% and R^2 value of 0.53 (Fig. 6). The performance of the model differed for good and poor management practices of the farmers. The difference between simulated and observed yield was less for those farmers whose management practices were according to recommendations. Planting time, plant population, number of irrigation, irrigation at critical stages, fertilizer application dates, application at crop critical stages, weed management, and disease control were better in the case of progressive farmers' fields and the model also simulated almost the same yield as that observed.

APSIM–Rice

The APSIM-Oryza-2000 was evaluated with farmers' field data. Model performed well with an R^2 of 0.44, a RMSE of 440, and a d-stat of 0.78 for the final yield for 155 farmers' fields (Fig. 7). The performance of model was different for different farmers. The performance of the model was different for different farmers. The reason for this difference was the management practices of the farmers and different amounts of inputs. The difference between simulated and observed yield was less for those farmers who used recommended cultural practices to grow their crops.

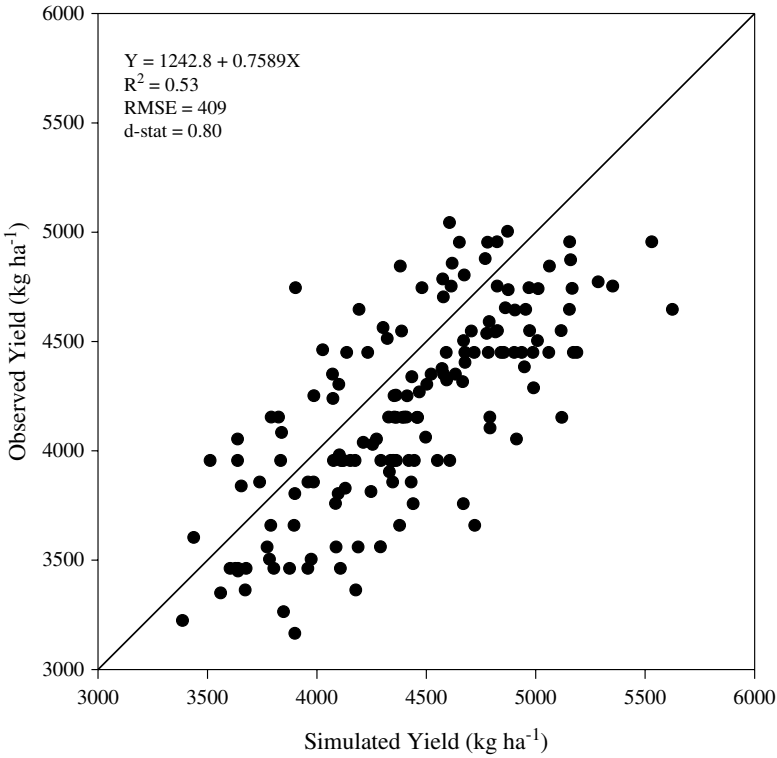


Fig. 6. Relationship between observed and simulated yield in 155 farmers rice fields (using DSSAT) in five strata of the rice–wheat cropping zone of Punjab.

DSSAT–Wheat

The CSM-CERES-Wheat model was evaluated with data from 155 farmers' fields to predict wheat yield. A close agreement was observed between the simulated and observed for farmers' yield. When models were evaluated at the farmers' field data, goodness of model (R^2) was 0.64 for CSM-CERES-Wheat between observed and simulated yield of 155 farmers as shown in Fig. 8. Comparison of individual farmers' yields showed that DSSAT simulated wheat yield with percent error ranging from –25% to 17% having RMSE 436 kg ha^{-1} and d-statistic of 0.87. Overall, the DSSAT model predicted the yield with an error of 1.6% and bias was calculated as 0.98. The difference between simulated and observed yield was less for those farmers who were growing wheat according to agriculture department recommendations. Good cultural practices by progressive farmers were the key factors in better simulation by the model.

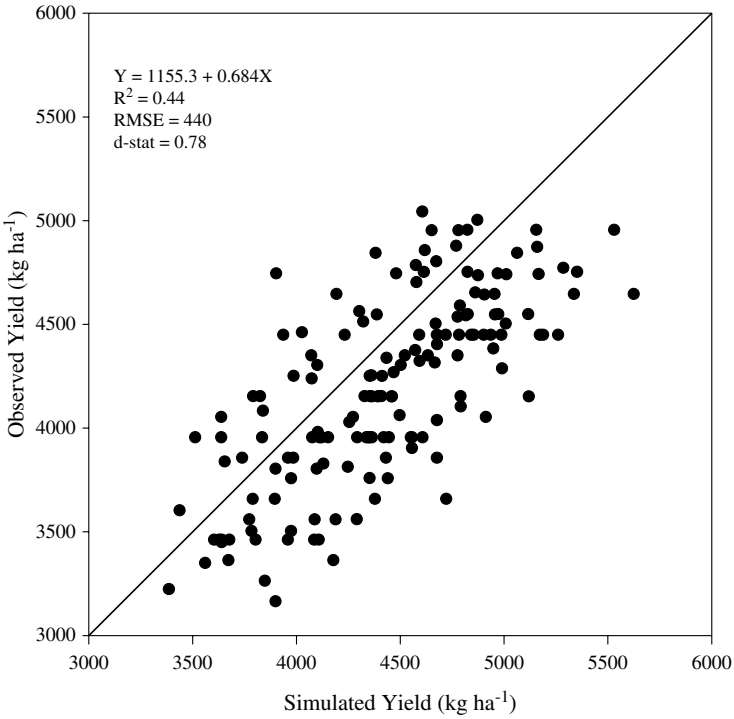


Fig. 7. Relationship between observed and simulated yield in 155 farmers rice fields (using APSIM) in five strata of the rice–wheat cropping zone of Punjab.

APSIM–Wheat

The APSIM–Wheat was evaluated with field data of 155 farmers of five regions. The relationship was drawn between farmers' observed yields and the simulated yield of wheat by APSIM. The model performed well with an R^2 value of 0.37, an RMSE of 592, and a d-stat of 0.88, as shown in Fig. 9. APSIM–wheat simulated yield with more error as compared to DSSAT as the value for RMSE was slightly higher. So far as the value of R^2 was concerned, it was less than CSM-CERES-Wheat which showed that the performance of CSM-CERES-Wheat was slightly better as compared to APSIM. However, the wheat data from the farmers' fields had the same uncertainty as the rice data.

Economic analysis

The Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD) Version 6.0.1 Beta was used to determine the impact of climate change on

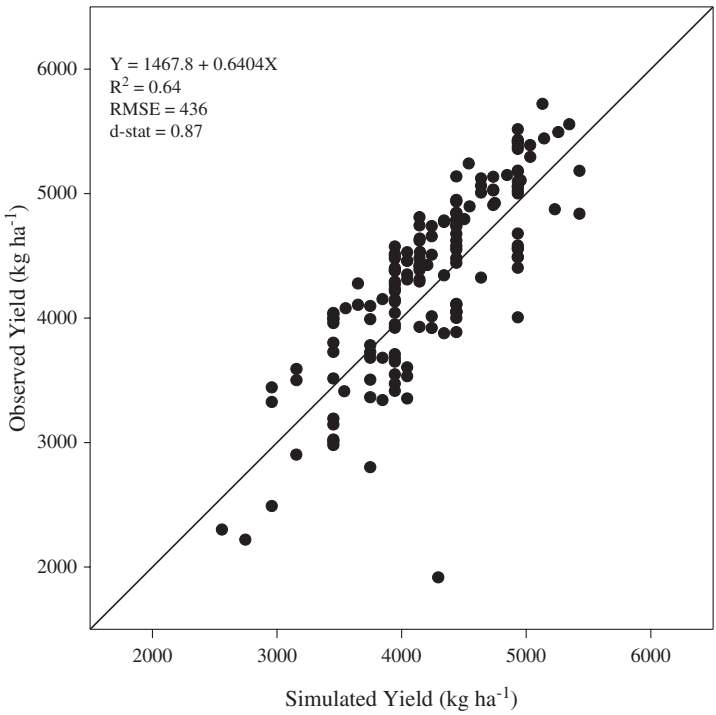


Fig. 8. Relationship between observed and simulated yield in 155 farmers wheat fields (using DSSAT) in five strata of the rice–wheat cropping zone of Punjab.

socio-economic indicators. It simulates technology adoption and impact in a population of heterogeneous farm households. Farmers are assumed to be economically rational and thus choose between management systems based on expected economic returns. This model uses data on the spatial variability in economic returns to represent heterogeneity in the farm population. One of the important implications of this model is that incomplete adoption of a new technology can simply be due to heterogeneity in farming conditions such as soils, climate, water, costs, and the farm household's characteristics in technology adoption analysis.

Most of the literature attributes incomplete adoption to attitudes such as risk aversion or constraints like access to the technology or finance that are typically difficult to observe and quantify (Suri, 2011). While these factors may indeed contribute to low adoption rates in some cases, in several cases observable heterogeneity in biophysical and economic characteristics of farms can be sufficient to explain low adoption rates (Antle *et al*., 2005). In climate change assessment, the TOA-MD model implies that all farms are not affected in the same way; in most cases, some farms lose and some farms gain from climate change. Similarly, some farms may be willing to adopt technologies that facilitate adaptation

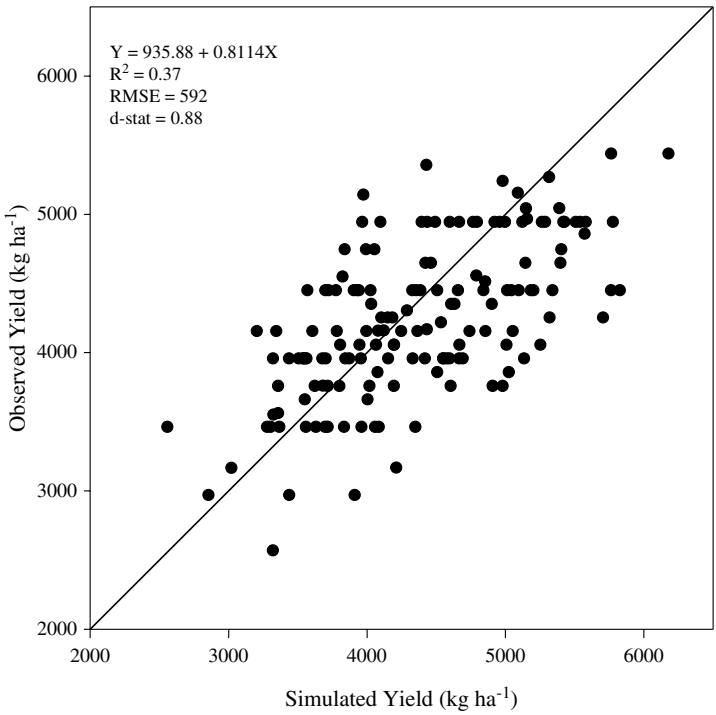


Fig. 9. Relationship between observed and simulated yield in 155 farmers wheat fields (using APSIM) in five strata of the rice–wheat cropping zone of Punjab.

to climate change, while others will not. The TOA-MD model allows researchers to simulate the impacts of the full range of adoption rates from 0% to 100%. In this study, farmers are presented with a simple binary choice: They can operate with a current or base production "System 1", or they can switch to an alternative "System 2".

Under the climate change analysis, it is necessary to distinguish between three factors that affect the expected value of a production system: The production methods used, referred to here as the technology, the physical environment in which the system is operated, i.e., the climate, and economic and social environment in which the system is operated, namely, the socio-economic setting that has been referred to as representative agricultural pathways (RAPs) (Rosenzweig *et al.*, 2013b). These RAPs are basically qualitative storylines that can be translated into model parameters such as farm and household size, prices, and costs of production and policy. A major challenge in scenario design for climate impact assessment is the dimensionality of the analysis. Farmers are initially operating a base technology with a base climate known as "System 1", while "System 2" is defined as the case in which farmers continue using the base technology under a perturbed climate. There is also

a "System 3", which is defined as an adapted technology used to withstand the adverse impacts of perturbed climate.

The analysis was conducted for each of 5 GCMs discussed previously. Their overall impacts were observed in each scenario for both the DSSAT and APSIM crop model outcomes and for livestock. Three core questions were answered through the analyses. In Core Question 1, sensitivity of current agricultural production system to climate change was assessed. Impact of climate change on future agricultural production was addressed in Core Question 2. Core Question 3 aimed to find out benefits of potential adaptations to climate changes (Rosenzweig *et al*., 2013b). First, climate change impact assessments (CC-IA) were made without using the RAPs to find out the sensitivity of current agricultural production system to climate change (Core Question 1). After applying the RAPs the analyses were again carried out for evaluating the impacts of climate change on future production system (Core Question 2). Then analysis was made for future adapted production system by using RAPs and adaptations to address Core Question 3. The outputs of the rice and wheat simulations of DSSAT and APSIM were used as inputs of TOA-MD.

Data used for economic analysis

The data used for TOA-MD analysis for the base system is given in the form of the averages of all selected farms. The average farm size of the sample in the study area was 4.5 ha with coefficient of variation (CV) of 0.5, while the average yields of rice and wheat crops were 18,349 and 18,915 kg, with standard deviation of 9435 and 9840 kg, respectively, on a per farm basis. The output price per kg was Rs. 43 for rice and Rs. 29 for wheat with standard deviation of 0.3 and 0.4, respectively. The cost of production for rice was Rs. 533.725 with standard deviation of Rs. 293,186 per farm and for wheat it was Rs. 338,396 with standard deviation of Rs. 187,340 per farm. Mean net farm returns for rice and wheat crops were Rs. 256,558 and Rs. 204,804 per farm, with standard deviation of Rs. 187,329 and 165,076, respectively. These values can be converted into USD at the rate of USD1 = Rs. 94.68.

Outreach Activities and Interaction with Stakeholders

Stakeholder interactions and key decisions

Regional RAPs were developed by conducting two meetings with interdisciplinary stakeholders including economists, plant breeders, irrigation specialists, soil scientists, agronomists, plant pathologists, entomologists, policymakers, progressive farmers, extensionists, and other experts. A nested approach was followed to develop RAP scenarios and the framework to follow for the development of RAPs was based on intermediate challenges (SSP2) (O'Neill *et al.*, 2012) with an optimistic scenario

Table 3. Key adaptation matrix under optimistic scenario for rice–wheat cropping system of Punjab.

Biophysical factors	Policy variables	Socio-economic	Others
1. Change in cropping pattern (e.g. in some areas rice can be replaced by sunflower, sorghum, and millet) 2. Short stature and duration wheat varieties 3. Improved cultivars to survive water and heat stress and excessive frost etc. 4. Improved agri. practices (resource conservation technologies, high-efficiency irrigation system, integrated pest management, etc.)	1. Ground water/surface water policies 2. Subsidy on critical inputs (specially fertilizers) 3. Efficient input/output markets 4. Government investments in agriculture (infrastructure, research and development) 5. Implementation of "good agricultural practices" especially for rice 6. Supportive trade policies 7. Farm consolidation	1. Diversification to avoid risk 2. Optimal use of inputs 3. Participatory management approach 4. Off-farm income opportunities 5. Agroforestry	1. Use of IT tools (climate/ market data, etc.) 2. Agroclimatic advisory services for farmers 3. Establish and strengthen interaction among stakeholders

in the mid-century time-period (2040–2069). Key variables for RAPs for the different categories including biophysical, policy, institutional, and socio-economic indicators, etc. were defined and discussed in these meetings (Table 3). The first meeting for RAP development with stakeholders was conducted on May 15, 2013 at the University of Agriculture, Faisalabad, Pakistan. Parameters like input cost and output prices required revision and consensus was achieved in the next meeting with the same team members. The second meeting on RAP development with stakeholders was conducted on June 6, 2013 in the same place.

Based on the defined time-period (2040–2069) for the rice–wheat zone of Punjab, a RAP entitled "Rice and Wheat Production under Vulnerable Climatic Conditions" and a short narrative for each of the RAPs was constructed. The economics team identified key parameters that were likely to affect the study area for the mid-century scenario (2040–2069). Regional-level pathways were reviewed and consulted for consistency with higher-level RAPs. Based on this consistency check, and agreement and confidence levels among team members, the above steps were repeated in subsequent meetings of all stakeholders which involved field experts, researchers,

policymakers, and farmers for a broader consensus on these scenarios. After consensus, full RAP narratives were documented and distributed to other experts and scientists for their comments. These final RAPs were used by crop and economic modeling teams for parameter quantification and scenario development for further use in the analysis. These RAPs for rice–wheat cropping system will be available for other impact assessment studies in the future.

While constructing the RAPs, unavailability of region specific *ex-ante* analytical impact assessments studies for crop and livestock was one of the major issues. For this reason it was difficult sometimes to adjust the RAPs with global model trend factors for different socio-economic indicators. Minor crops and livestock activities (meat and milk) were included in the RAPs without any modeled data (like IMPACT trends). For the future, such modeled estimates are required to generate regional-level RAPs and make them consistent with the global-level RAPs.

Representative agricultural pathways (RAPs)

From the biophysical indicators, soil degradation, ground and surface water availability, changing climate, overall productivity, pest and disease infestation, and livestock units/household were discussed in detail regarding their direction and magnitude of change and rationale. Similarly for socio-economic indicators, land availability, human population growth, household size, investments in agriculture, livestock contribution, and off-farm income impacts were discussed. Different important policy options such as subsidies for critical inputs, and policy interventions especially for groundwater use and marketing were also debated and included in the RAPs. In the case of technology, improved post-harvest management practices, proper usage of IT tools, and change in cropping pattern were discussed in detail. The complete details of all indicators and their concerned variables are described in the DevRAP Matrix. DevRAPS tool was developed by Valdivia and Antle (2012) in an Excel spreadsheet. It provides as structure to record and document the information in a systematic manner and then it is used for quantitative scenarios development. The specific version developed for using in TOA-MD has been designed to provide

Table 4. Quantification of scenarios for TOA-MD for the rice–wheat cropping system of Punjab.

			% Change	
Serial No.	Variable	Direction of change	Rice	Wheat
1	Average household size	Increase	40	40
2	Non-agricultural income	Increase	40	40
3	Price of output	Increase	65	70
4	Variable production cost	Increase	55	50

Table 5. Quantification of scenarios for crop models (DSSAT and APSIM) for rice and wheat crops on the basis of the adaptation package developed for the rice–wheat cropping zone of Punjab.

Serial No.	Variable	Direction of change	% Change	
			Rice	Wheat
1	Nitrogen/hectare (kg)	Increase	15	25
2	Sowing density (plant/m^2)	Increase	15	30
3	Irrigation	Decrease	15	25
4	Sowing dates	Decrease	5 Days	15 Days

a structured format for the parameters of the economic and crop simulation models (Part 1, Chapter 5 in this volume). The adaptation information described in the DevRAP Matrix was used to develop the crop management scenarios for the crop simulation models and the simulated yield and associated variables were then used as input for the TOA-MD model (Tables 4 and 5).

Sensitivity of Current Agricultural Production Systems to Climate Change

The changing climate is amplifying the current vulnerabilities of the farmers, especially those who depend on semi-subsistence agriculture for their livelihood (Claessens *et al*., 2012). In this section the result of TOA-MD analysis, using a "current technology, perturbed climate" scenario for the mid-century time-period, i.e., 2040–2069 is discussed. In the first step of economic analysis, effects of future climate and current production system were analyzed for productivity and socio-economic indicators. For each GCM, gains, losses, and net impacts as a percentage of mean net returns for Core Question 1 are given in Fig. 10. The results of climate change impacts simulated using crop models are given in Table 6.

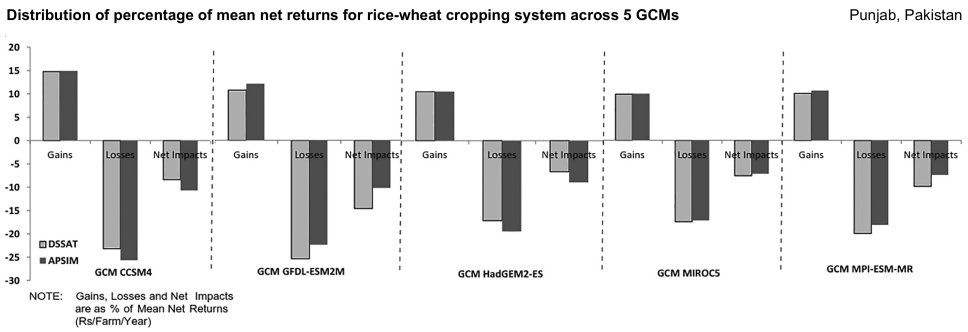


Fig. 10. Distribution of gainers and losers (percentage) for five GCMs using DSSAT and APSIM crop models for the rice–wheat cropping system of Punjab (answering Core Question 1).

Table 6. Climate sensitivity of current agricultural production systems for the rice–wheat cropping system of Punjab (answering Core Question 1).

Aggregated results (for all 155 farms)	GCM CCSM4		GCM GFDL-ESM2M		GCM HadGEM2-ES		GCM MIROC5		GCM MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Observed mean output of wheat (kg/farm)	18,915	18,915	18,915	18,915	18,915	18,915	18,915	18,915	18,915	18,915
Mean change in output of wheat (%)	−6.2	−11.4	−12.8	−11.5	−16.9	−12.3	−19.0	−10.6	−14.7	−11.2
Observed mean output of rice (kg/farm)	18,349	18,349	18,349	18,349	18,349	18,349	18,349	18,349	18,349	18,349
Mean change in output of rice (%)	−12.5	−16.6	−30.1	−19.2	−8.1	−19.3	−12.3	−16.0	−20.5	−14.6
Observed mean milk production (liter/farm/annum)	3,267	3,267	3,267	3,267	3,267	3,267	3,267	3,267	3,267	3,267
Mean change in milk production (%)	−12	−12	−12	−12	−12	−12	−12	−12	−12	−12
Losers (%)	68.9	72.3	82.6	76.0	71.1	75.4	74.2	73.2	78.1	72.5
Gains (% mean net returns)	14.8	14.9	12.6	14.3	14.6	14.6	14.5	14.7	13.8	14.6
Losses (% mean net returns)	−23.2	−25.7	−29.9	−26.3	−23.8	−27.0	−25.6	−25.2	−27.2	−24.7

(*Continued*)

Table 6. (*Continued*)

Aggregated results (for all 155 farms)	GCM CCSM4		GCM GFDL-ESM2M		GCM HadGEM2-ES		GCM MIROC5		GCM MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Observed net returns without climate change (Rs./farm/year)	547,316	547,316	547,316	547,316	547,316	547,316	547,316	547,316	547,316	547,316
Predicted net returns with climate change (Rs./farm/year)	485,170	468,369	424,337	456,637	477,659	455,588	463,805	468,113	447,646	471,393
Observed *per capita* income without climate change (Rs./person/year)	70,726	70,726	70,726	70,726	70,726	70,726	70,726	70,726	70,726	70,726
Predicted *per capita* income with climate change (Rs./person/year)	63,666	60,706	56,791	59,464	62,427	59,569	60,386	61,180	59,162	61,488
Observed poverty rate without climate change (%)	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
Predicted poverty rate with climate change (%)	33.1	36.6	37.7	36.3	33.9	36.9	35.9	36.2	36.0	35.2

Note: Poverty line = USD 1.25/person/day and USD 1= Rs. 94.68, season or time duration = 365 days.

The observed mean production of wheat is 18,915 kg per farm across the study area. The reduction in mean production for DSSAT ranged from 6–19% while for APSIM it ranged from 10–12% for all 5 GCMs. In the case of rice, the production was 18,349 kg per farm for the study area. The reduction in mean production for DSSAT ranged from 8–30% while for APSIM it ranged from 14–19%. These percentages show the changes in mean farm productions. In case of livestock, observed mean production of milk was 3,267 liters per farm for all GCMs with a reduction in production of about 12% for Core Question 1, which is about finding the sensitivity of current agricultural production systems to climate change. Income from the sale of animals was added in the non-agricultural income in the farm sheet for the economic analysis since dairy farming was one of important activity in the study area. The same pattern for livestock income was found for Core Questions 2 and 3. The analyses of these core questions assessed the impacts of climate change on future agricultural production systems and the benefits of climate change adaptations.

Depending upon the distribution of costs and benefits across the area, the analysis showed that number of losers ranged from 69 to 83% for DSSAT and from 72 to 76% for APSIM, due to perturbed climate. These losers are basically the farmers who were worse off economically under the perturbed climate. Overall vulnerability can be measured by the proportion of farmers made worse off relative to some threshold like the poverty line. A poverty line of USD 1.25 per day was used for analysis. Percentage gains and losses for DSSAT ranged from 13 to 15% and 23 to 30%, respectively, while for the case of APSIM percentage gains and losses ranged from 14 to 15% and from 25 to 27%, respectively. These gains and losses were estimated as percent of mean net farm returns. The observed net returns without climate change for both DSSAT and APSIM were Rs. 0.54 million per farm. However, with the adverse climate change, the predicted net returns varied from Rs. 0.42 to 0.48 million per farm for DSSAT and from Rs. 0.45 to 0.47 million per farm for APSIM for all five GCMs. Observed *per capita* income without climate change would be about Rs. 70,000 per person per year for all cases, while with climate change it would reduce and would vary between Rs. 56,000 and 63,000 per person per year for DSSAT and Rs. 59,000 and 61,000 per person per year for APSIM, respectively. Without climate change poverty rate would be 29%, while in the case of climate change predicted poverty rate would increase and show a range from 33 to 38% for DSSAT and from 35 to 37% for APSIM.

The Impacts of Climate Change on Future Agricultural Production Systems

The second stage of the economic analysis was to compare the "System 1", i.e., future production system and current climate with "System 2", i.e., future production

system and future climate in mid-century (2040–2069) for rice–wheat cropping system by using five GCMs. These analyses were conducted to evaluate the isolated role of climate impacts for the selected cropping system using adaptation scenarios. The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) (Nelson *et al.*, 2010) was used for price and yield trend factors for wheat and rice crops. The IMPACT model data were used with regional RAPs. These trends were in real terms based on 2005 in USD in order to make the regional RAPs consistent with the global RAPs. The yields trends based on IMPACT for rice and wheat were 139 and 126%, respectively. Price trends for wheat and rice crops used for without climate change case were 127 and 119%, and for with-climate-change case these values were 133 and 125%, respectively. In the case of cost trends, values for wheat and rice were 139 and 125%, respectively. Livestock productivity and prices was trended by using the regional RAPs developed for the rice–wheat cropping system of Punjab.

Gains, losses, and the net impacts for each GCM were estimated to find out the impacts of climate change on future agricultural production systems (Fig. 11). The projected wheat production is 26,473 kg per farm for all cases of Core Question 2 (Table 7). The reduction in wheat mean production ranged from 6.2 to 19% for DSSAT and from 10.6 to 12.3% for APSIM. In the case of the rice crop, the projected production was 25,073 kg per farm for all analyses of Core Question 2 (Table 7). The reduction in rice mean production ranged from 8 to 30% for DSSAT, while for APSIM it ranged from 14 to 19%. In case of livestock, projected mean milk production was 3,267 litres per farm for all analysis and the reduction in production was 12% for all cases of Core Question 2.

The percentage of farmers who would lose their farm income ranged from 57 to 70% for the DSSAT crop model simulations and from 61 to 71% for the APSIM crop simulations for all five GCMs. For DSSAT the percentage gains would be 11

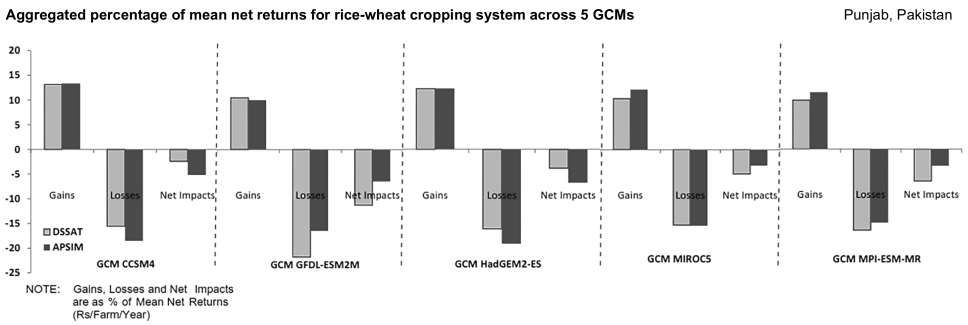


Fig. 11. Aggregated gains and losses for five GCM climate change scenarios with DSSAT and APSIM for stimulated yields in the rice–wheat cropping system of Punjab (answering Core Question 2).

Table 7. Impact of climate in future without adaptation for the rice–wheat cropping system of Punjab (answering Core Question 2).

Aggregated results (for all 155 farms)	GCM CCSM4		GCM GFDL-ESM2M		GCM HadGEM2-ES		GCM MIROC5		GCM MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected mean output of wheat (kg/farm)	26, 473	26, 473	26, 473	26, 473	26, 473	26, 473	26, 473	26, 473	26, 473	26, 473
Mean change in output of wheat (%)	−6.2	−11.4	−12.8	−11.5	−16.9	−12.3	−19.0	−10.6	−14.7	−11.2
Projected mean output of rice (kg/farm)	23, 238	23, 238	23, 238	23, 238	23, 238	23, 238	23, 238	23, 238	23, 238	23, 238
Mean change in output of rice (%)	−12.5	−16.6	−30.1	−19.2	−8.1	−19.3	−12.3	−16.0	−20.5	−14.6
Projected mean milk production (litre/farm/annum)	3, 757	3, 757	3, 757	3, 757	3, 757	3, 757	3, 757	3, 757	3, 757	3, 757
Mean change in milk production (%)	−12.0	−12.0	−12.0	−12.0	−12.0	−12.0	−12.0	−12.0	−12.0	−12.0
Losers (%)	57.0	63.2	78.2	70.9	61.5	67.6	66.4	60.7	70.9	61.8
Gains (% mean net returns)	13.2	13.4	10.6	10.1	12.5	12.5	12.4	14.6	11.5	13.4
Losses (% mean net returns)	−15.6	−18.5	−22.0	−16.6	−16.3	−19.4	−18.3	−18.4	−19.1	−17.3

(*Continued*)

Table 7. (*Continued*)

Aggregated results (for all 155 farms)	GCM CCSM4		GCM GFDL-ESM2M		GCM HadGEM2-ES		GCM MIROC5		GCM MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected net returns without climate change (Rs./farm/year)	1,143,902	1,143,902	1,143,902	1,143,902	1,143,902	1,143,902	1,143,902	1,143,902	1,143,902	1,143,902
Projected net returns with climate change (Rs./farm/year)	1,107,119	1,066,232	973,614	1,042,692	1,083,949	1,040,572	1,052,664	1,081,443	1,027,911	1,080,171
Projected *per capita* income without climate change(Rs./person/year)	103,030	103,030	103,030	103,030	103,030	103,030	103,030	103,030	103,030	103,030
Projected *per capita* income with climate change(Rs./person/year)	100,233	94,873	89,433	93,190	97,862	93,316	94,465	97,319	93,370	96,496
Projected poverty rate without climate change (%)	16.5	16.5	16.5	16.5	16.5	16.5	16.5	16.5	16.5	16.5
Projected poverty rate with climate change (%)	16.6	19.1	19.1	18.8	17.3	19.2	18.6	18.5	18.2	18.1

Note: Poverty line = USD 1.25/person/day and USD 1= Rs. 94.68, season or time duration = 365 days.

to 13% and percentage loss would be from 16 to 22%, respectively. For APSIM the percentage gains would be 10 to 15% and percentage loss would be from 17 to 19%, respectively. Projected farm net returns based on the trends and RAPs are Rs. 1.14 million per farm per year. Projected net returns with climate change ranged from Rs. 0.97 to 1.1 million per farm for DSSAT and from Rs. 1.04 to 1.08 million per farm for APSIM. The projected *per capita* income without climate change would be Rs. 103,000 per person per year for all GCMs and both crop models. However, under climate change, *per capita* income ranged from Rs. 89,000 to 100,000 per person for DSSAT crop simulations and from Rs. 93,000 to 97,000 for the APSIM simulations. Without climate change poverty rate would be 16% for both crop models, while under climate change poverty rates would slightly increase and range from 17 to 19% for DSSAT and from 18 to 19% for APSIM.

Evaluation of Potential Adaptation Strategies

Finally, the impacts of adaptation strategies on the distribution of potential adopters and non-adopters were analyzed using TOA-MD to answer Core Question 3. For analysis, in "System 1" RAPs were included and in "System 2" RAPs and adaptation package were included for the rice–wheat system based on the crop model simulations of DSSAT and APSIM. This analysis was basically for the future, in which non-adopted and adopted production systems were compared. It is clear that after implementing the adaptations strategies, the vulnerabilities of future cropping systems to climatic change have been reduced to a large extent and these adaptations have a significant impact on the rice–wheat cropping zone of Punjab.

In the Core Question 3, the benefits of climate change adaptations were assessed. The projected production of wheat would vary from 21,583 to 24,819 kg per farm for DSSAT and 23,166 to 23,657 kg per farm for APSIM across the study area in adaptation scenario analyses (Table 8). Mean change in wheat production ranged from 10.2 to 22.6% for DSSAT and from 30.6 to 39.2% for APSIM for all five GCMs. In the case of rice, projected production without adaptation ranged from 16,126 to 21,427 kg per farm for DSSAT and from 18,560 to 20,401 kg per farm for APSIM. Mean change in production for DSSAT ranged from 9.9 to 20.1%, while for APSIM it ranged from 1.7 to 24%. In the case of livestock, projected mean milk production without adaptation was 3,593 litres per farm for all GCMs and its mean yield increase was 42% for all cases.

The percentage adopters for the DSSAT crop simulations ranged from 69 to 74% and for APSIM from 70 to 81%. For DSSAT, the projected net returns without adaptation ranged from Rs. 0.97 to 1.1 million per farm per year and with adaptation ranged from Rs. 1.17 to 1.32 million per farm per year. For APSIM the projected

Table 8. Analyzing the benefits of climate change adaptations for the rice–wheat cropping system of Punjab (answering Core Question 3).

Aggregated results (for all 155 farms)	GCM CCSM4		GCM GFDL-ESM2M		GCM HadGEM2-ES		GCM MIROC5		GCM MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected mean output of wheat without adaptation (kg/farm)	24, 819	23, 423	22, 959	23, 351	21, 966	23, 167	21, 584	23, 628	22, 887	23, 657
Mean change in output of wheat (%)	10.2	36.1	16.3	33.6	21.8	39.2	22.6	32.2	13.7	30.6
Projected mean output of rice without adaptation (kg/farm)	20, 179	19, 353	16, 126	18, 560	21, 427	18, 675	20, 397	20, 401	18, 368	19, 650
Mean change in output of rice (%)	9.9	1.7	11.0	3.7	15.6	17.3	20.1	24.0	11.4	6.1
Projected mean milk production without adaptation (liter/farm/annum)	3, 593	3, 593	3, 593	3, 593	3, 593	3, 593	3, 593	3, 593	3, 593	3, 593
Mean change in milk production (%)	42	42	42	42	42	42	42	42	42	42
% adoption rate	69.3	69.9	72.3	74.8	73.6	78.3	73.9	80.1	70.4	75.5

(*Continued*)

Table 8. (*Continued*)

Aggregated results (for all 155 farms)	GCM CCSM4		GCM GFDL-ESM2M		GCM HadGEM2-ES		GCM MIROC5		GCM MPI-ESM-MR	
	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM
Projected net returns without adaptation (Rs./farm/year)	1,107,119	1,066,232	973,614	1,042,692	1,083,950	1,040,572	1,052,664	1,081,443	1,027,911	1,080,171
Projected net returns with adaptation (Rs./farm/year)	1,298,473	1,290,330	1,179,490	1,283,586	1,322,573	1,343,998	1,305,660	1,391,876	1,224,112	1,320,155
Projected *per capita* income without adaptation (Rs./person/year)	100,234	94,873	89,433	93,190	97,862	93,316	94,465	97,319	93,370	96,496
Projected *per capita* income with adaptation (Rs./person/year)	117,042	114,702	107,654	114,534	118,912	120,319	118,198	124,939	110,884	117,448
Projected poverty rate without adaptation (%)	16.6	19.1	19.1	18.8	17.3	19.2	18.6	18.5	18.2	18.1
Projected poverty rate with adaptation (%)	15.0	16.0	17.2	16.6	14.6	16.2	15.3	15.5	16.3	15.9

Note: Poverty line = USD 1.25/person/day and USD 1= Rs. 94.68, season or time duration = 365 days.

net returns without adaptation ranged from Rs. 1.04 to 1.08 million per farm and with adaptation it ranged from Rs. 1.28 to 1.39 million per farm per year. For DSSAT projected *per capita* income without adaptation would be from Rs. 89 to 100 thousand and with adaptation it would be from Rs. 107 to 118 thousand per person per annum. In case of APSIM projected *per capita* income for without adaptation cases would be between Rs. 93 to 97 thousand and with adaptation it would range from Rs. 114 to 125 thousand per person per annum. Without adaptation poverty would range from 17 to 19% for the DSSAT crop simulations and from 18 to 19% for the APSIM crop simulations, while, with adaptation the poverty rate would slightly decrease to 15 to 17% for both crop simulation models.

Conclusions

Pakistan is exposed to five major risks related to climate change comprising rise in sea level, glacial retreats, floods, higher average temperature, and an increase in the frequency of droughts. Its economy is dependent upon agriculture and these climatic risks are major threats to the sustainability of agricultural systems. Any negative impacts would be devastating not only for the socio-economic conditions of the rural population but would also jeopardize the country's food security. It is therefore important to quantify the impact of climate change in agriculture using an interdisciplinary approach.

The findings of this study showed that the performance of the crop simulations DSSAT and APSIM for simulating rice and wheat yield was good. For rice, DSSAT simulated yield of 155 farms with an R^2 of 0.52, a RMSE of 425 kg ha^{-1}, and a d-stat of 0.78, while for APSIM the R^2 was 0.42, the RMSE was 440 kg ha^{-1}, and the d-stat was 0.78. For wheat, DSSAT simulated yield with an R^2 of 0.64, a RMSE of 436 kg ha^{-1}, and the d-stat was 0.87, while for APSIM the R^2 was 0.37, a RMSE of 592 kg ha^{-1}, and a d-stat of 0.88, respectively. Due to climate change, there is a mean reduction of 15.2 and 17.2% in rice yield by DSSAT and APSIM, respectively. In wheat, mean yield reduction was 14.0% in DSSAT and 13.76% in APSIM with five GCMs, respectively.

By using TOA-MD, future socio-economic indicators were estimated for the impact of climate change on current and future agricultural production systems in mid-century (2040–2069). TOA-MD also allows us to obtain a measure of vulnerability in terms of the proportion of farms that would lose under climate change. It was estimated that if the current production technology prevails in the future, there would be about 69–83% of farms that would likely be vulnerable to climate change. Poverty rate with climate change would be between 33 and 38%. Quantification of climate change impacts on future agricultural production systems calculated that

there would be 57–71% losers, and that poverty rates would range between 17 and 19%. In the light of these results, it is clear that climate change could negatively impact future crop and livestock production and farm returns. However, adaptation strategies could have a significant positive impact in reducing the vulnerabilities due to climate change. Potential adopters of the adaptation strategies ranged from 69 to 81%, and poverty rates could be reduced from 15 to 17% after the implementation of the adaptation strategies.

References

Ahmad, S. (2006). *Effect of agro-environmental factors on growth, yield and quality of fine (Basmati-385)*, PhD thesis, Dept. Agron. University of Agriculture, Faisalabad, Pakistan.

Ahmad, S. A., Soler, C. M. T., Ali, H., Zia-Ul-Haq, M., Anothai, J., Hussain, A., Hoogenboom, G., and Hasanuzzaman, M. (2012). Application of the CSM-CERES-Rice model for evaluation of plant density and nitrogen management of fine transplanted rice for an irrigated semiarid environment, *Precision Agric*., **13**, 200–218.

Ahmad, S. A., Ali, H., Hussain, A., Garcia, A. G., Khan, M. A., Zia-Ul-Haq, M., Hasanuzzaman, M., and Hoogenboom, G. (2011). Application of the CSM-CERES-Rice model for evaluation of plant density and irrigation management of transplanted rice for an irrigated semiarid environment, *Irrig. Sci.*, **31**(3), 491–506.

Ahmad, S. and Hasanuzzaman, M. (2012). Integrated effect of plant density, N rates and irrigation regimes on the biomass production, N content, PAR use efficiencies and water productivity of rice under irrigated semiarid environment, *Not. Bot. Horti. Agrobo.*, **40**(1), 201–211.

Ahmad, S., Ahmad, A., Zia-ul-Haq, M., Ali, H., Khaliq, T., Anjum, M. A., Khan, M. A., Hussain A., and Hoogenboom, G. (2009). Resources use efficiency of field grown transplanted rice (*Oryza sativa* L.) under irrigated semiarid environment, *J. Food Agric. Environ*., **7**(2), 487–492.

Antle, J. M., Valdivia, R. O., Crissman, C. C., Stoorvogel, J., and Yanggen, D. (2005). Spatial heterogeneity and adoption of soil conservation investments: integrated assessment of slow formation terraces in the Andes, *J. Inter. Agric. Trade Develop*, **1**(1), 29–53.

Asian Development Bank (2009). Building climate resilience in the agriculture sector in Asia and in the Pacific, *ADB Report*, 1–9. Available at: www.adb.org/publications/building-climate-resilience-agriculture-sector-asia-and-pacific. Accessed on 15 January 2014.

Blunden, J. and Arndt, D. S. (eds.) (2012). State of the Climate in 2011, *Bull. Am. Meteorol. Soc*., **93**(7), 1–264.

Buckthought, L., Snow, V., Shepherd, M., Clough, T., Cameron, K., and Di, H. (2011). "Nitrogen fertilizer and urine patch interaction-use of APSIM to aid experimental design", in Currie, L. D. and Christensen, C. L. (eds.), *Adding to the knowledge base for the nutrient manager*, Occasional Report No. 24, Fertilizer and Lime Research Centre, Massey University, Palmerston North, New Zealand. p. 13.

Chaudhry, Q. Z. and Rasul, G. (2004). Agroclimatic classification of Pakistan. *Sci, Vis*., **1**(2–4), 59–66.

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., and Herrero, M. (2012). A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data, *Agric. Syst.*, **111**, 85–95.

Gaydon, D. S., Probert, M. E., Buresh, R. J., Meinke, H., Suriadi, A., Dobermann, A., Bouman, B., and Timsina, J. (2012). Rice in cropping systems-modelling transitions between flooded and non-flooded soil environments, *Eur. J. Agron.*, **39**, 9–24.

Ghazala, N. and Rasul, G. (2009). Water Requirement of Wheat Crop in Pakistan, *Pak. J. Meteorol*., **6**(11), 89–97.

Gitay, H., Suarez, A., Watson, R. T., Anisimov, O., Chapin, F. S., Cruz, R. V., Finlayson, M., Hohenstein, W. G., Insarov, G., Kundzewicz, Z., Leemans, R., Magadza, C., Nurse, L., Noble, I., Price, J., Ravindranath, N. H., Root, T. L., Scholes, B., Villamizar, A., and Rumei, X. (2002). Climate change and biodiversity, Intergovernmental Panel on Climate Change, Geneva, April 2002, IPCC Technical Paper V, **77**. Available at: www.ipcc.ch/pdf/technical-papers/climate-changes-biodiversity-en.pdf. Accessed on 15 June 2014.

Government of Pakistan (2010). *Agricultural Census of Pakistan, Report*, Statistics Division, Agricultural Census Organization, Lahore, Pakistan. Available at: www.pbs.gov.pk. Accessed on 1 July 2014.

Government of Pakistan (2013). *Economic survey of Pakistan 2013*, Ministry of Food, Agric. and Livestock, Economic wing, Islamabad, Pakistan. Available at: ww.finance.gov.pk. Accessed on 1 July 2014.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas, *Int. J. Climatol*., **25**, 1965–1978.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J. (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5.1.023 -Stub* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Hoogenboom, G. (2000). Contribution of agrometeorology to the simulation of crop production and its applications, *Agric. Forest Meteorol*., **103**, 137–157.

Hunt, L. A. and Boote, K. J. (1998). "Data for model operation, calibration, and evaluation", in Tsuji, G. Y., Hoogenboom, G., and Thornton, P. K. (eds.), *Understanding Options for Agricultural Production*, Kluwer Academic, Dordrecht, the Netherlands, pp. 9–39.

Iqbal, S., Ahmad, A., Hussain, A., Ali, M. A., Khaliq, T., and Wajid, S. A. (2008). Influence of transplanting date and nitrogen management on productivity of paddy cultivars under variable environments, *Int. J. Agric. Biol*., **10**, 288–292.

Janjua, P. Z., Samad, G., and Khan, N. U. (2010). Impact of climate change on wheat production: A case study of Pakistan, *Pak. Dev. Rev*., **49**(4), 2, 799–822.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). DSSAT Cropping System Model, *Eur. J. Agron.*, **18**, 235–265.

Kaiser, H. M. and Drennen, T. (1993). *Agricultural Dimensions of Global Climate Change*, St. Lucie Press, St. Lucie, FL.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM: A model designed for farming systems simulation, *Eur. J. Agron*., **18**, 267–288.

Kreft, S. and Eckstein, D. (2013). *Global climate risk index. Who Suffers Most from Extreme Weather Events? Weather-Related Loss Events in 2012 and 1993 to 2012*. Available at: www.germanwatch.org/en/cri. Accessed on 15 January 2014.

Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Mohamed, H., Fosu, K. Y., Gbetibouo, G., Jain, S., Mahamadou, A., Mano, R., Mariara, J. K., El-MarsafawyS., Molua, E., Ouda, S., Ouedraogo, M., Seïe, I., Maddison, D., Niggo, S., and Seo, A. (2006). Will African agriculture survive climate change?, *The World Bank Econ. Rev.*, 20, 367–388.

Mall, P. K. and Aggarwal, R. K. (2002). Climate change and rice yields in diverse agro-environments of India. I. Evaluation of impact assessment model, *Clim. Change*, **52**, 315–330.

Mendelsohn, R., Dinar A., and A. Sanghi (2001). The effect of development on the climate sensitivity of agriculture, *Environ. Develop. Econ*., **6**, 85–101.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., Vuuren, D. P. V., Carter, T. R., Emori, S., Kainuma, M., and Kram, T. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**, 747–756.

Nelson, G. C., Rosegrant, M. W., Palazzo, A., Gray, I., Ingersoll, C., Robertson, R., Tokgoz, S., Zhu, T., Sulser, T. B., Ringler, C., Msangi, S., and You, L. (2010). *Food Security, Farming, and Climate Change to 2050: Scenarios, Results, Policy Options.* Available at: www.ifpri.org. Accessed on 1 December 2013.

Nelson, G. C., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M., Magalhaes, M., Valmonte-Santos, R., Ewing, M., and Lee, D. (2009). Climate change: impact on agriculture and costs of adaptation, Food Policy Report 21, International Food Policy Research Institute (IFPRI), Washington, DC, USA.

O'Neill, B. C., Carter, T. R., Ebi, K. L., Edmonds, J., Hallegatte, S., Kemp-Benedict, E., Kriegler, E., Mearns, L., Moss, R., Riahi, K., Ruijven, B., and Vuuren, D. (2012). *Meeting report of the workshop on the nature and use of new socioeconomic pathways for climate change research*, Boulder, CO, November 2–4, 2011.

Rasul, G., Mahmood, A., Sadiq, A., Khan, S. I. (2012). Vulnerability of the Indus Delta to Climate Change in Pakistan, *Pak. J. Meteorol.*, **8**(16), 89–107.

Rosenzweig, C., Jones J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013a). Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Rosenzweig, C., Jones, J., Hatfield, J., Antle, J., Ruane, A., Boote, K., Thorburn, P., Valdivia, R., Porter, C., Janssen, S., and Mutter, C. (2013b). *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.0*. Available at: www.agmip.org. Accessed on 1 July 2014.

Ruane, A. C., Goldberg, R. and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol.*, 200. doi: 10.1016/j.agr.formet.2014.09.016.

Sarkar, R. and Kar, S. (2006). Evaluation of management strategies for sustainable rice-wheat cropping system, using DSSAT seasonal analysis, *J. Agric. Sci.*, **144**, 421–434.

Seo, N. and Mendelsohn, R. (2008). A Ricardian analysis of the impact of climate change on South American farms, *Chil. J. Agric. Res*., **68**, 69–79.

Stone, L. F. and Heinemann, A. B. (2012). Simulation of nitrogen management in upland rice with ORYZA/APSIM 2000 model, *Revista Brasileira de Engenharia Agricola e Ambiental*, **16**, 611–617.

Suri, T. (2011). Selection and Comparative Advantage in Technology Adoption, *Econometrica*, **79**(1), 159–209.

Taylor, K. E., Stouffer, R. J., and Meehl, G.A. (2012). An overview of CMIP5 and the experiment design, *Bull. Am. Meteorol. Soc*., **93**(4), 485–498.

Valdivia, R. O. and Antle, J. M. (2012). *DevRAP: A Tool for Designing Representative Agricultural Pathways and Scenarios*. Available at: http://tradeoffs.oregonstate.edu. Accessed on 21 March 2014.

Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. O. (2004). Guidelines for use of climate scenarios developed from statistical downscaling methods, 1–27. Available at: www.ipcc-data.org/guidelines/dgm_no2_v1_09_2004.pdf. Accessed on 21 March 2014.

Yang, Y., Watanabe, M., Zhang, X., Zhang, J., Wang, Q., and Hayashi, S. (2006). Optimizing irrigation management for wheat to reduce groundwater depletion in the piedmont region of the Taihang Mountains in the North China Plain, *Agric. Water Manage.*, **82**(1–2), 25–44.

Chapter 8

Integrated Climate Change Assessment through Linking Crop Simulation with Economic Modeling — Results from the Indo-Gangetic Basin

Nataraja Subash[1], Harbir Singh[1], Babooji Gangwar[1], Guillermo Baigorria[2], Alok Kumar Sikka[3], and Roberto O. Valdivia[4]

[1]*ICAR–Project Directorate for Farming Systems Research, Modipuram, Uttar Pradesh, India*

[2]*University of Nebraska-Lincoln, Lincoln, NE, USA*

[3]*Indian Council of Agricultural Research, New Delhi, India*

[4]*Oregon State University, Corvallis, OR, USA*

Introduction

Climate change impacts are increasingly visible in South Asia (SA), with greater variability of the monsoon. Seasonal mean rainfall shows interdecadal variability, noticeably a declining trend with more frequent deficit monsoons (Kulkarni, 2012). There has also been an increase in the occurrence of extreme weather events such as heat waves and intense precipitation that affect agricultural production and thereby the food security and livelihoods of many small and marginal farmers, particularly in the more stress-prone regions of the central and eastern Indo-Gangetic Plain (IGP). The frequency of heavy precipitation events are increasing (Krishnamurthy *et al.*, 2009; Pattanaik and Rajeevan, 2010; Rajeevan *et al.*, 2008; Sen Roy, 2009), while light-rain events are decreasing (Goswami *et al.*, 2006). It is projected that under RCP4.5, the temperature increase at the 75th percentile will be 1.1°C and 3.0°C during Rabi season (December to February) in 2035 and 2100, respectively, and the corresponding precipitation will also increase on the order of 4% and 14%. However, during Kharif season (June to August), the increase of temperature will be 0.9°C

and 2.4°C in 2035 and 2100, respectively, and the corresponding precipitation will also increase on the order of 6% and 13% (IPCC, 2013). In a recent study under the Coupled Model Intercomparison Project (CCMI) Phase 5, projected under the business-as-usual scenario, mean warming in India is likely to be in the range of 1.7–2.0°C by the 2030s and 3.3–4.8°C by the 2080s relative to pre-industrial times, and precipitation may increase by 4–5% by the 2030s and 6–14% by the 2080s compared with the 1961–1990 baseline (Chaturvedi *et al*., 2012).

Simulation models for rice production indicate a reduction in yield of about 5% per degree rise in mean temperature above 32°C. Aggarwal and Mall (2002) observed that a 2°C increase resulted in a 15% to17% decrease in grain yield of rice and wheat and that the decrease was even higher in wheat. Simulations of the impact of climate change on wheat yields for several locations in India using a crop modeling approach indicated that in northern India, a 1°C rise in the mean temperature had no significant effect on potential yields, whereas a rise of 2°C reduced potential grain yields in most places (Aggarwal and Sinha, 1993). As glaciers melt, river runoff will initially increase in winter or spring but eventually will decrease as a result of loss of ice resources (IPCC, 2007). Consequences for downstream agriculture, which relies on this water for irrigation, will be likely unfavorable in most South Asian countries.

In the future, public health, biodiversity, agricultural production, food security, access to drinking water, migration, and even regional geo-political stability are likely to be affected. Climate change is also likely to affect various sectors, including (1) the public budget, which is needed for climate change adaptation (e.g., for flood control, afforestation, and re-forestation, climate-proofing infrastructure, and pollution control), including the development of disaster risk management plans; (2) terms of trade (e.g., effects on hydropower exports, falling agricultural yields, reduced labor productivity, and faster natural resources depletion); and (3) welfare of the population (i.e., price increases, flooding, pollution, and health impacts).

With the growing challenges to provide food security for growing populations in the region, it is pertinent to utilize farming system approaches that integrate cropping systems with alternative income-generating activities. Traditionally, the farming systems of the region were sustainable; however, these farming systems are changing rapidly from extensive mixed crops and livestock to intensive irrigated crops. This signifies the need for optimization of various agricultural components and their integration into multi-enterprise farming systems, development of sustainable farming practices for enhanced soil health, and resource-use efficiencies under diverse farming situations and farm categories. Site-specific and integrated-system (cropping, livestock, fisheries, and vegetables) management options can reduce the climatic risk and improve utilization of available natural resources that contribute to higher agricultural productivity and thereby enhance the food and livelihood security of small-scale and marginal farmers of the region. Integrated assessment of

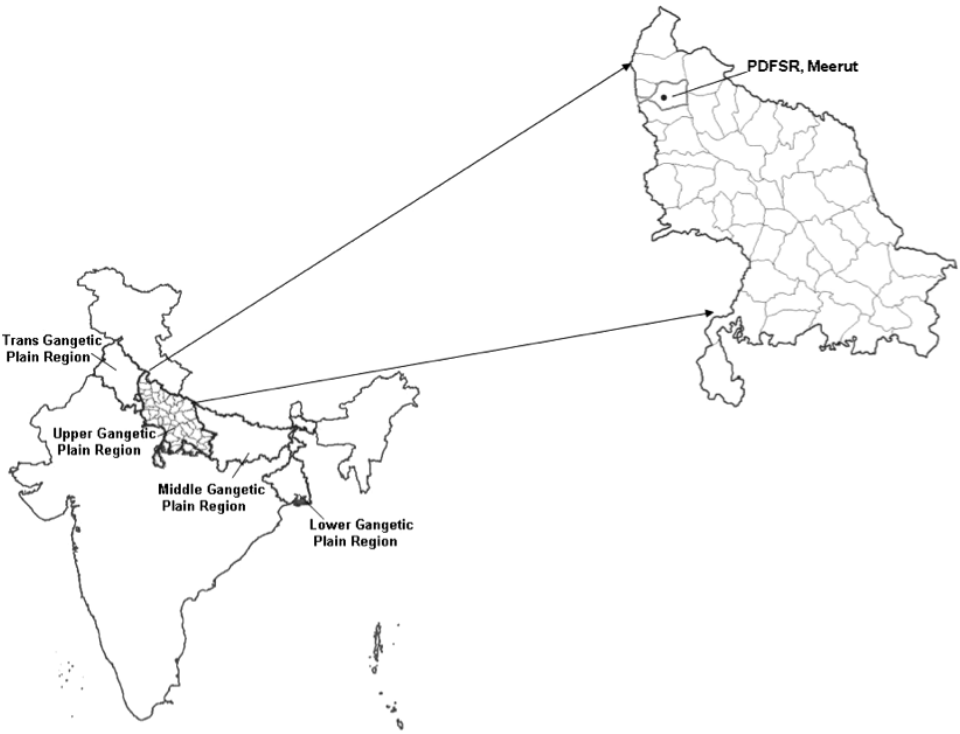


Fig. 1. The Indo-Gangetic Plains in India, indicating agroclimatic zones and the location of the study site in Meerut district, Uttar Pradesh, India.

climate change impacts on agricultural systems through modeling provides meaningful estimates to help policymakers to develop constructive and concrete national and regional plans for projected future conditions.

Farming System Investigated

Settings and locations

The study area is located in Meerut (29°4′ N, 77° 46′ E, 237 m), part of the Upper Gangetic agroclimatic region of the Indo-Gangetic Plains (IGP), India (see Fig. 1).

Climate and soil data

The climate is semi-arid subtropical, with dry hot summers and cold winters. Meteorological data were collected from the agrometeorological observatory located at the Project Directorate for Farming Systems Research, Modipuram, near to the experimental site, during the period 1992–2010. Data collected include daily maximum and minimum temperatures, rainfall, and sunshine hours. The solar

radiation was estimated based on sunshine hours, by using the Ängstrom equation (Ängstrom, 1924; Medugu and Yakubu, 2011). The climate data for the period 1980–1991 were created using the bias-corrected AgMERRA (Modern-Era Retrospective Analysis for Research and Applications, Ruane *et al.*, 2014) satellite-derived data. The climatic scenarios for 20 global climate models (GCMs) were generated through the R-codes provided by AgMIP (Ruane and Hudson, 2013).

The soil of the experimental site is a sandy loam (18% clay, 19.5% silt, and 62.5% sand) of Gangetic alluvial origin. It is very deep (>2 m), well drained, flat (about 1% slope), and representative of an extensive soil series, i.e., the Sobhapur series of northwest India. Soil physical and chemical characteristics data (*viz.*, bulk density, electrical conductivity, pH, organic carbon, ammonical nitrogen and nitrate nitrogen) were determined for different depths (0–15, 15–30, 30–45, 45–60, 60–75, 75–90, and 90–105 cm). Soil texture, field capacity (drained upper limit), and 15-bar lower limit at different depths were also determined (Table 1).

Farming system

Rice–wheat and sugarcane–wheat are the predominant cropping systems in the area, with livestock being an integrated part of the farming system of sample households. However, in this present study we have considered only the rice–wheat farms of each households. Livestock holding is generally proportional to land holding but the majority of the farmers, even with tiny land holdings, keep at least one milch animal (indigenous or crossbred cow and/or buffalo). The study site has excellent irrigation facilities with almost 99% cultivable area being irrigated. The typical farming system followed in this region is depicted in Fig. 2.

Table 1. Physical and chemical properties of the soil profile at the experimental site at Modipuram.

Depth (cm)	Sand %	Silt %	Clay %	Texture[1]	Bulk density mg/m^3	pH	EC[2] dS/m	OC[3] %	NH_4-N kg/ha	NO_3-N kg/ha
0–15	65.4	27.5	7.1	sl	1.52	8.01	0.11	0.47	13.5	8.17
15–30	70.4	22.5	7.1	sl	1.54	7.89	0.12	0.40	14.6	8.08
30–45	70.4	20.0	9.6	sl	1.62	7.91	0.10	0.34	15.3	9.03
45–60	65.4	22.5	12.1	sl	1.59	7.85	0.11	0.35	14.7	8.36
60–75	65.4	20.0	14.6	sl	1.62	7.78	0.10	0.19	10.2	6.17
75–90	70.4	15.0	14.6	sl	1.62	7.79	0.13	0.16	9.7	5.47
90–105	67.9	17.5	14.6	sl	1.64	7.72	0.12	0.13	7.3	4.80

[1]sl = sandy loam; [2]electrical conductivity; [3]organic C.
(Adopted from Subash *et al.*, 2014.)

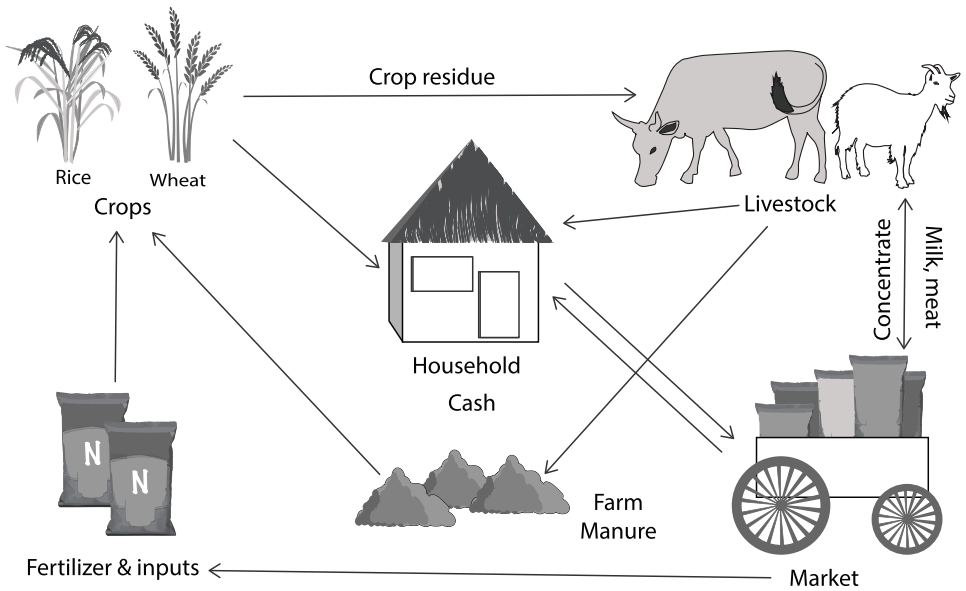


Fig. 2. Typical farming system followed in the Meerut district of northwest India.

Stakeholder Interactions, Meetings, and Representative Agricultural Pathways

Stakeholder interactions and meetings

To develop the representative agricultural pathways (RAPs) of the study region, a stakeholders' brainstorming session was organized at the Indian Council of Agricultural Research (ICAR) — Project Directorate for Farming Systems Research (PDFSR), Modipuram on July 18, 2013. The meeting was chaired by the project director and team leader of the AgMIP–ICAR collaborative project. This meeting was attended by researchers, academics, policymakers, and agricultural development officials from the state agricultural departments and farmers from the district. The participating stakeholders included researchers from Sardar Vallabhbhai Patel University of Agriculture and Technology, Modipuram; Central Potato Research Institute Regional Station, Modipuram; Project Directorate on Cattle, Modipuram; Shobhit University, Modipuram; and PDFSR, Modipuram. Officers from district agricultural/horticultural offices, progressive farmers, etc. also participated. In addition to this, the deputy director general (education) and the deputy director general (extension) of ICAR also provided their input during regional research team (RRT) mid-term and finish-line workshops. Based on these inputs and discussions, RAPs for the study site were developed.

Representative Agricultural Pathways (*RAPs*)

RAPs provide an overall narrative description of a plausible future development pathway, and also contain key variables with qualitative storylines and quantitative trends, consistent with higher-level pathways (e.g. SSPs, global RAPs developed by the AgMIP Global Modeling Group). Prices, policy, and productivity trends should be consistent with the higher-level RAPs or scenarios that are available (SSPs, global RAPs, CCAFS regional scenarios). RAPs are translated into one or more scenarios (parameterizations) for TOA-MD (Tradeoff Analysis Model for Multi-dimensional Impact Assessment) and crop models. These scenarios represent a set of technology and management adaptations to climate change. These scenarios, developed for specific RAPs, will typically include changes in the types of crops or livestock produced and the way they are managed (e.g., use of fertilizers and improved crop cultivars). Procedures for RAP development are based on the step-wise process as described in Valdivia and Antle (2014).

Outside experts may need to be consulted if there is an important area of expertise not represented within the team. These scenarios help to constrain uncertainty in each region, allow stakeholders and policymakers to assess explicit risks, and contribute to monitoring, evaluation, and decision-making. The methodological framework for the engagement of stakeholders in the development of RAPs is given in Fig. 3.

The future trends in the agricultural system was developed by the RRT and was shared with the stakeholders (see Box 1). Though it was difficult to focus the discussion around major biophysical, socio-economic, and technology variables, farmers expressed concern about declining farm profitability as well as government apathy (as perceived by farmers) for addressing their problems such as high prices of agricultural inputs; mainly seed, fertilizer, agricultural labor, transportation cost, and inadequate marketing facilities. The stakeholders, particularly farmers, expressed their opinion on many other issues not directly related to the farm sector. During the RAP development process, it was learnt that eliciting the desired information from such a diverse group of stakeholders requires time, patience, and mutual understanding in order to develop useful and realistic RAPs.

Data and Methods of Study

Climate

Observed trends in temperature and precipitation

The decadal trends in meteorological parameters showed significant decreasing trend of June rainfall of the order of −50.3 mm/decade; this may affect the level of groundwater, and farmers are forced to go deep for pumping to get irrigation water. This

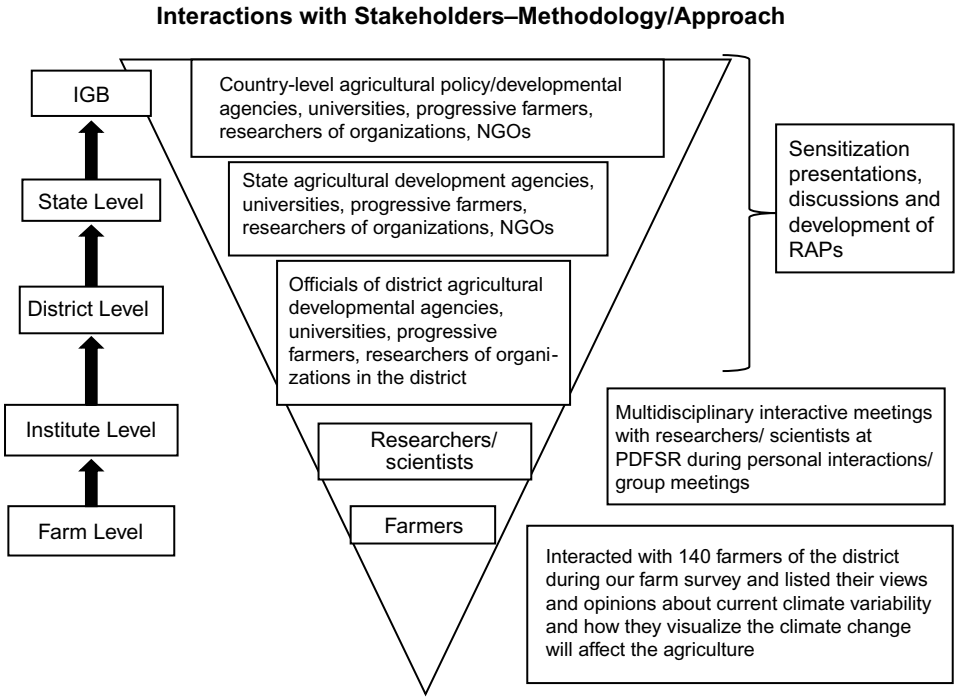


Fig. 3. The RAP development process for the AgMIP regional integrated assessment in the IGB, India.

Box 1. Example of RAPs generated for cereals production system under climate change.

The agricultural production system in the Indo-Gangetic region where rice–wheat is the predominant cropping system that contributes substantially to national food security. Rice–wheat production in the region is adversely affected by climate change. Farm productivity declines and agricultural labor moves out (out-migration) to other sectors in search of better wages. Though the government adopts long-term and short-term policy measures, rice–wheat production costs increase substantially. Imports are inadequate to meet domestic demand. Incentives in the form of assured prices (minimum support prices) are inadequate to enhance agricultural production to meet food demand. Hence, the government liberalizes imports of food grains, invests in food chain logistics, and boosts research and development for developing new crop cultivars to boost agricultural production for ensuring food security.

leads to higher input costs. The bright sunshine hours showed decreasing trends in all months except May and June, which will be highly detrimental for rice productivity by lowering the dry matter accumulation. In the case of wheat, a significant increasing trend of maximum temperature during March and April could be one of the reasons for decreasing wheat grain yields. The increasing trend of maximum temperature during the milking/dough stage may result in forced maturity, which decreases the grain size and thereby grain yield.

Climate projections

All five GCMs predicted higher mean monthly maximum and minimum temperatures during the mid-century period (2040–2069) under RCP8.5 compared to the baseline (1980–2010) (Fig. 4). However, as far as rainfall projections are concerned, there is a lot of uncertainty among the GCM predictions, particularly during the monsoon months (Fig. 5). The crop growing season temperature and rainfall also showed large uncertainty among the GCMs, especially precipitation change compared to baseline (Table 2). Since 80% of the total annual rainfall is received during the July to September monsoon season, a decrease of rainfall would affect the groundwater level and therefore require more energy to pump water.

Crops

Crop model calibration (*DSSAT and APSIM*)

The Agricultural Production Systems Simulator (APSIM)7.5 crop model was already calibrated by Subash *et al.* (2014) for the same rice and wheat varieties and the same .XML files were used for the AgMIP simulations. In the case of the Decision Support System for Agrotechnology Transfer (DSSAT) 4.5, the genetic coefficients reported in Pathak *et al.* (2003) for the same rice and wheat varieties were used.

Crop model results (*DSSAT and APSIM*)

Both APSIM and DSSAT simulated higher wheat yields compared to survey data after the 20% cumulative probability level (Fig. 6). Since both crop models simulate yield without considering pest and diseases effects, the simulated yields are always higher than actual survey yield data. However, up to the 60% cumulative probability level, DSSAT simulated higher yields compared to APSIM. The differences in simulated wheat yield at higher and lower cumulative probability levels between APSIM and DSSAT may be due to the difference in sensitivity of the two crop models in extreme management situations (i.e., under higher/lower management inputs than recommended management practices). In the case of rice, both DSSAT and APSIM

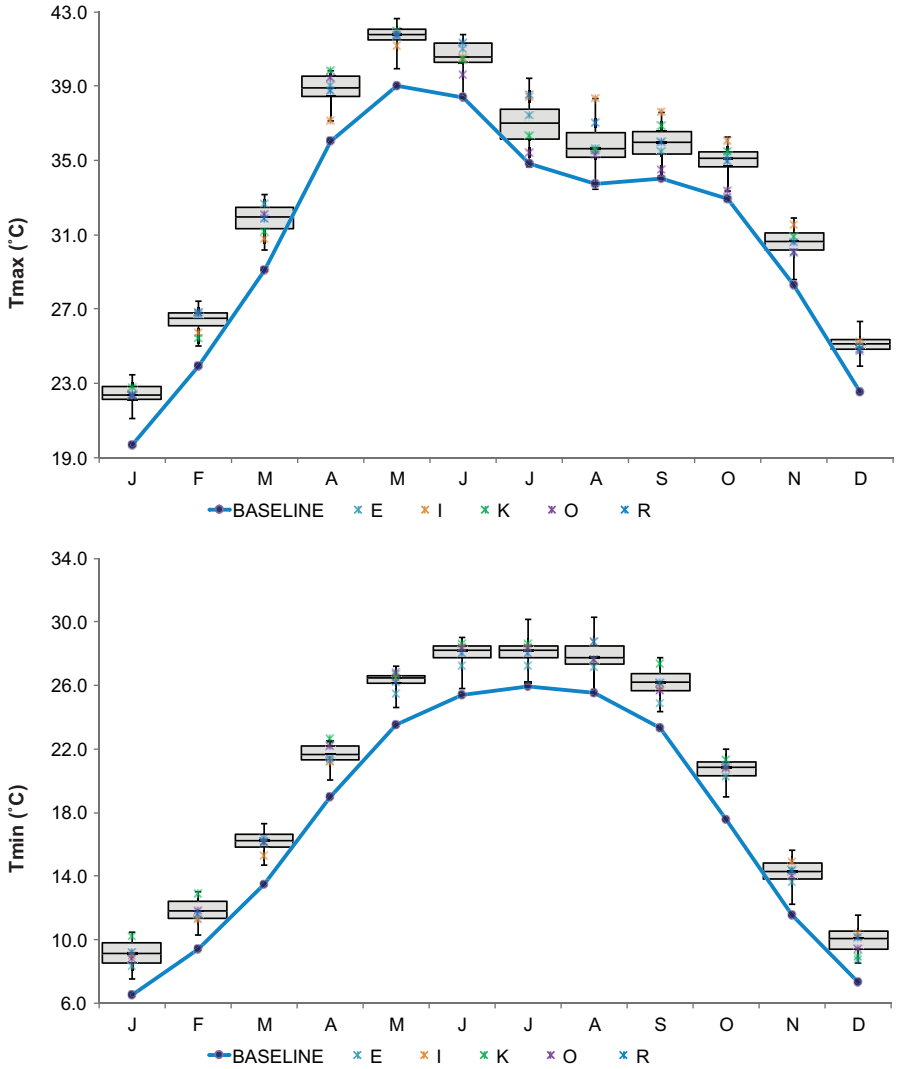


Fig. 4. Baseline (line and dots) and future (box-and-whisker plots) monthly and seasonal mean maximum and minimum temperature for Modipuram, India, in the 2050s under RCP8.5 for 20 GCMs. The stars represent the five GCMs (E-CCSM4, I-GFDL-ESM2M, K-HadGEM2-ES, O-MIROC5, and R-MPI-ESM-MR) used in the integrated assessment.

models overestimated yields compared to observed farm survey data. Moreover, DSSAT simulated higher rice yields than did APSIM.

There is variability among the simulated impacts of climate change on rice and wheat by different GCMs and between the two crop models, DSSAT and APSIM (Fig. 7). Differences between the DSSAT and APSIM projections are due to differences in sensitivity of the crop models to increases in CO_2 and temperature. In the

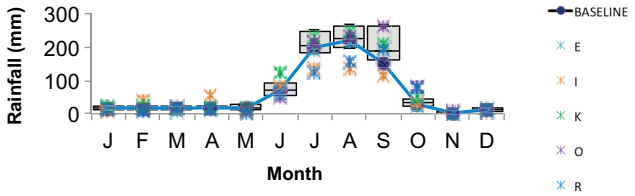


Fig. 5. Baseline (line and dots) and future (box-and-whisker plots) monthly mean precipitation for Modipuram, India, in the 2050s under RCP8.5 for 20 GCMs. The stars represent the five GCMs (E-CCSM4, I-GFDL-ESM2M, K-HadGEM2-ES, O-MIROC5, and R-MPI-ESM-MR) used in the integrated assessment.

Table 2. Climate changes for 2050s compared to historical period for five targeted GCMs.

	GCM CCSM4 E	GCM GFDL-ESM2M I	GCM HadGEM2-ES K	GCM MIROC5 O	UKMO HadGEM2-ES R
Growing season temperature change for wheat (°C)	1.9	2.8	2.9	2.4	2.9
Growing season precipitation change for wheat (%)	−23.0	26.2	6.1	−13.9	−18.4
Growing season temperature change for rice (°C)	2.4	2.9	2.2	1.7	2.7
Growing season precipitation change for rice (%)	3.1	−25.6	29.6	26.6	−8.4

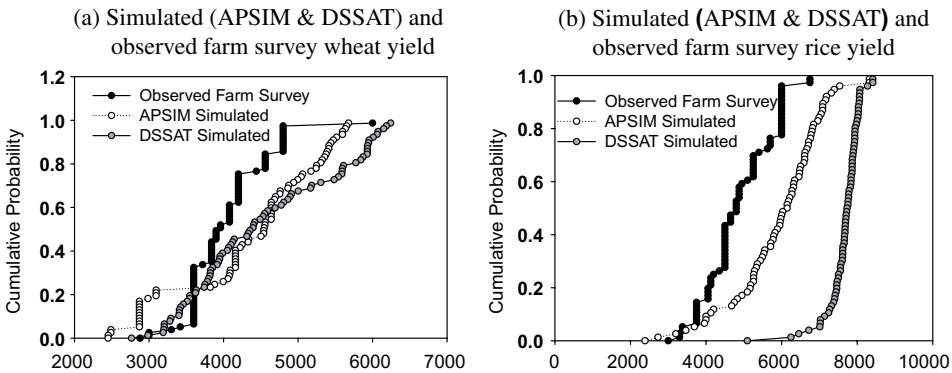


Fig. 6. Cumulative distribution functions for observed farm survey wheat and rice yields, and APSIM and DSSAT simulated rice and wheat yields.

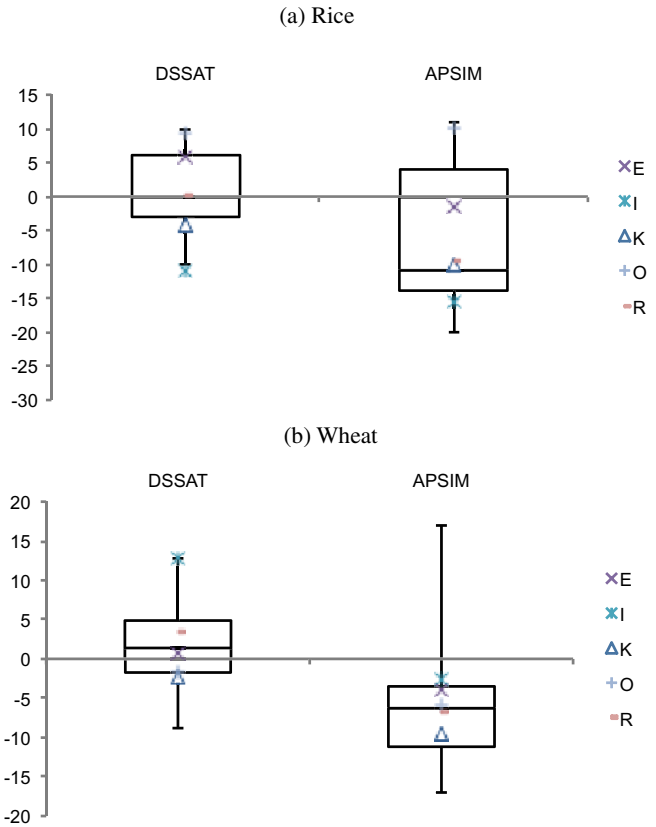


Fig. 7. Distribution of mean yield changes (%) from 20 GCM-based climate change scenarios using mean-only delta scenarios for APSIM and DSSAT simulation outputs. The five GCMs that are the focus of the core simulations are represented as stars.

case of rice, out of the 20 GCMs there is a 50% positive response in DSSAT-rice; however, in the case of APSIM-rice, 65% of the GCMs projected a pessimistic scenario. The range of variability is 9.4% increase to 10.8% decrease in projected yield by DSSAT, while APSIM projects a 10.6% increase to 15.6% decrease. In the case of wheat, 60% of the GCMs provided optimistic results through DSSAT while only 10% of the GCMs provided optimistic scenarios through APSIM. Overall, DSSAT simulated more optimistic projections than APSIM for both rice and wheat.

Economics

Survey data

This study is based on the farm survey (2012) data relating to 76 rice–wheat growing farm households in Meerut district of northwest India in the IGB. The average family

size of the sample households was 6.32, and average operational land holding was 1.68 ha, which is representative of the district. Wheat is grown on about 88,000 ha while rice is planted on 17,000 ha in the district. The average land area earmarked for rice is 0.29 ha with present yield level of 2365 kg/ha, while average area under wheat on sample households is 0.45 ha with present wheat yield of 3743 kg/ha.

Parameters emerging from the RAPs

Notwithstanding the divergence in the understanding of various stakeholders about the challenges facing the agriculture sector by mid-century, the following variables were identified through the RAP development process for use in TOA-MD simulations. The TOA-MD model is a unique simulation tool for multi-dimensional impact assessment that uses a statistical description of a heterogeneous farm population to simulate the adoption and impacts of a new technology or a change in environmental conditions (Antle and Valdivia, 2012; Claessens *et al*., 2012).

- Costs of crop production would increase by 20%.
- Farm size and herd size would decline by 10%, while family size would increase by 20% (Table 3).
- Off-farm employment opportunities would lead to an increase of about 50% in non-farm income.
- Income from livestock/dairy will be proportional to holding size. However, the majority of small and marginal farmers would keep at least one milch animal. Although the herd size would decline, past trend shows that growth in milk production would be around 15% because of most farmers' preference for high-yielding milch animals.
- On the basis of district-level data on average milk productivity, livestock holding and prevailing prices, it is estimated that a farmer with one hectare of land holding

Table 3. RAP parameters used for TOA-MD simulations.

RAP parameters	Direction of change	Magnitude (%)
Variable cost of production	Increase	20
Farm size	Decrease	10
Herd size	Decrease	10
Milk yield	Decrease	10
Non-farm income	Increase	50
Rice yield trend factor	Increase	149.49
Rice price trend factor	Increase	119.20
Wheat yield trend factor	Increase	139.93
Wheat price trend factor	Increase	126.81

would get an income of about Rs. 70,000 per year from livestock enterprise (mainly from selling milk).

- Expert opinions as well as research estimates indicate that milk production is likely to decline by 10–20% due to climate change impact. For TOA-MD simulations, the decline in milk production is estimated to be 10% (Table 2).
- For setting up TOA-MD model, required data were obtained from multi-model (APSIM and DSSAT) yield simulations, farm survey, secondary data on crop area and productivity, and growth trends in yields and prices (IFPRI-IMPACT model).
- The yield and price trend factor used for rice was 1.49497 and 1.192007, respectively. The trend factor used for wheat yield and price was 1.3993 and 1.2681, respectively. Since the IMPACT model did not provide cost trend, it was assumed that growth trend in cost would be proportional to AgMIP reference prices of rice and wheat.

Adaptation package

Based on stakeholder interactions and RAPs, the following adaptation strategies emerged to reduce the impact of climate change on wheat production. However, only one of these adaptation strategies (advancement of date of sowing in wheat by ten days from the present) has been incorporated in this study.

- Advancement of sowing date — ten days from the present.
- Use of short-duration rice and wheat varieties.
- Balanced fertilizer application in both rice and wheat.
- Modification of first date of irrigation in wheat.

AgMIP regional integrated assessment involves following three core research questions (Rosenzweig *et al*., 2014). The results pertaining to our study site are explained below.

Integrated Assessment of Climate Change Impacts in IGB

Impact of climate change on crop production

The current agricultural production system under a climate change scenario would experience a decline in mean rice yield from 8% to 23% with APSIM. However, DSSAT simulations shows both decline (4% to 19% under climate scenarios GFDL-ESM2M, HadGEM2-ES and MPI-ESM-MR) as well as increase in mean yield (2% to 5% for climate scenarios CCSM4 and MIROC5). In the case of wheat, the mean yield changes show a similar trend. APSIM estimates show decline in mean yield of wheat (17% to 29%), while DSSAT shows an increase in mean yield (6% to

15%). Accordingly, the percentage gains in mean net farm returns are higher under DSSAT (14% to 15%) than under APSIM (11% to 12%) in all five climate scenarios for the current agricultural production system.

Economic impact of climate change on current production systems

Overall, the mean net farm returns are likely to decline by 12% to 16% percent under APSIM and 4% to 8% under DSSAT under the five climate scenarios. Similarly, the *per capita* income would decline approximately by 8% to 10% and 2% to 6% as per APSIM and DSSAT estimates, respectively, under five climate scenarios. As a result of decline in mean net farm returns and *per capita* income, the population poverty rates would increase by about 1–3% under climate change. The decline in mean net farm returns is not large enough to have significant adverse impact on population poverty rate. Though it looks that population poverty rate increases only marginally (1–3%), it has wider implications as there is a large proportion of adversely affected farms (53–79% losers) under climate change (Table 4).

Core Question 2: What Is the Impact of Climate Change on Future Agricultural Production Systems?

Using RAP parameters and other estimates of productivity and price trends from a global model (IMPACT model) for rice and wheat, the TOA-MD analysis shows interesting results for climate change impacts. The losses in mean net farm return (23.4–25.4%) are higher than gains (18.5–21.3%) under APSIM, but DSSAT shows that gains in mean net farm return (23.8–28.6%) are little higher than losses (21–22%). Thus, under climate change, mean net farm return is likely to decline by about 3–9% (APSIM) whereas, DSSAT shows a little increase in mean net farm returns (2–8%) under five GCMs. The comparison between gains, losses, and net impacts under current agricultural production system and future agricultural production system (Q1 and Q2) by different climate scenarios and crop models is shown in Fig. 8. As expected, *per capita* income declines by 2–6% under APSIM but shows some increase under DSSAT (1–5%). It is interesting to note that even though yields decline substantially (under APSIM), there is only a small difference in the percentage of the population (1–3%) without and with climate change. This is logical because growth in prices offsets to a large extent the percentage decline in yields. Still, a large proportion of the population (39–64%) is vulnerable to climate change (Table 5). This leads to the question: What type of adaptation measures can be helpful to sustain farm incomes under climate change?

Table 4. Sensitivity of current agricultural production systems to climate change (Core Question 1).

	C1		C2		C3		C4		C5	
Aggregate results	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Observed mean yield (rice) (kg/ha)	2365	2365	2365	2365	2365	2365	2365	2365	2365	2365
Mean yield change (rice) (%) [defined as: (mean relative yield −1)*100]	−14	2	−23	−20	−9	−4	−12	6	−12	−10
Observed mean yield (wheat) (kg/ha)	3743	3743	3743	3743	3743	3743	3743	3743	3743	3743
Mean yield change (wheat) (%) [defined as: (mean relative yield −1)*100]	−17	6	−29	15	−24	7	−20	6	−24	7
Observed mean yield (livestock) (kg/animal/annum)	1485	1485	1485	1485	1485	1485	1485	1485	1485	1485
Mean yield change (livestock) (%)	−10	−10	−10	−10	−10	−10	−10	−10	−10	−10
Losers (%)	73.4	58.7	79.4	64.7	73.2	60.9	72.9	57.3	74.2	63.0
Gains (% mean net returns)	12.2	15.0	11.3	13.8	12.2	14.5	12.23	15.3	12.02	14.1
Losses (% mean net returns)	−21.4	−18.3	−23.6	−19.5	−21.3	−18.7	−21.22	−18.1	−21.64	−19.1
Observed net returns without climate change (Rs./farm)	37878	37879	37878	37879	37878	37879	37878	37879	37878	37879
Projected net returns with climate change (Rs./farm)	33187	36167	31709	34957	33233	35732	33306	36429	32998	35303
Observed *per capita* income without climate change (Rs.)	12281	12282	12281	12281	12281	12282	12281	12282	12281	12282
Projected *per capita* income with climate change (Rs.)	11340	11938	11043	11695	11349	11851	11363	11990	11301	11764
Observed poverty rate without climate change (%)	81.0	81.0	81.0	81.0	81.0	81.0	81.03	81.0	81.03	81.0
Projected poverty rate with climate change (%)	83.5	81.8	84.3	82.5	83.5	82.1	83.45	81.7	83.62	82.3

Note 1: C1–C5 = climate models, C1 = CCSM4, C2 = GFDL-ESM2M, C3 = HadGEM2-ES, C4 = MIROC5, C5 = MPI-ESM-MR; M1 crop model (APSIM), M2 = crop model (DSSAT).
Note 2: Poverty line for analysis is assumed Rs. 22812.50 *per capita*/annum, which is equivalent to USD1.25 per capita/day. National poverty line is Rs. 11000.
1USD = 55INR.

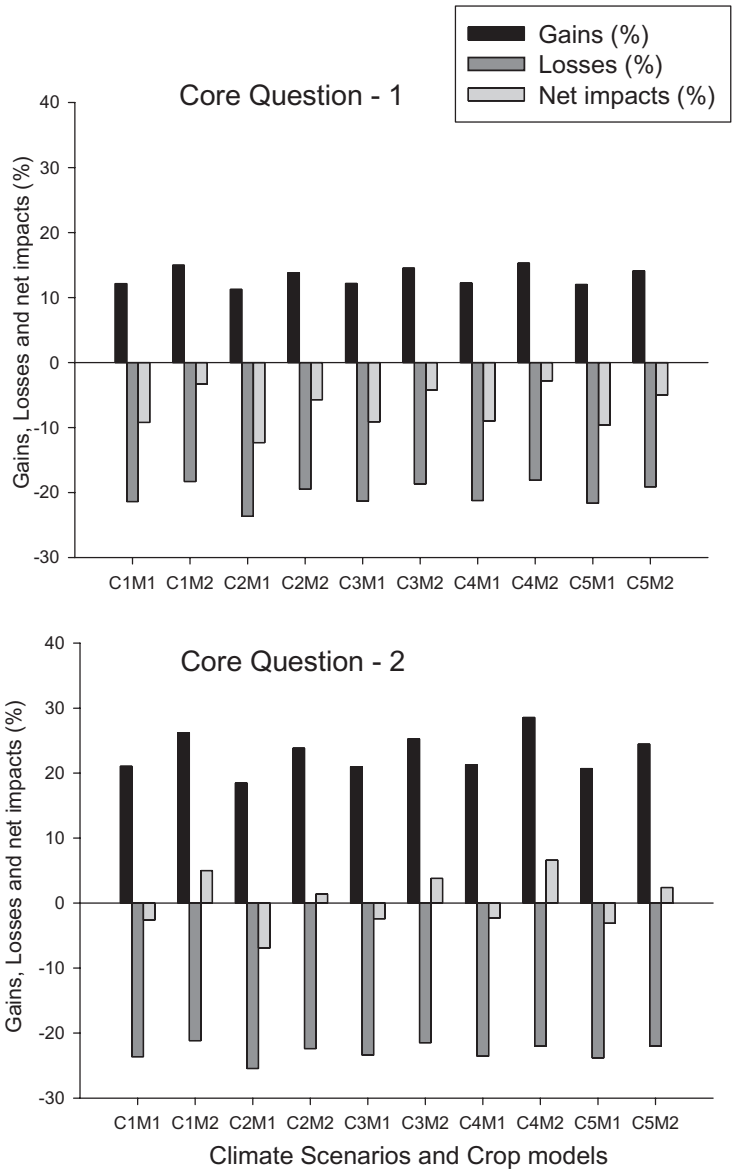


Fig. 8. Comparison between gains, losses, and net impacts under current agricultural production system and future agricultural production system (Q1 and Q2) by different climate scenarios and crop models. C1–C5 = climate models, C1 = CCSM4, C2 = GFDL-ESM2M, C3 = HadGEM2-ES, C4 = MIROC5, C5 = MPI-ESM-MR; M1 = crop model (APSIM), M2 = crop model (DSSAT).

Table 5. Impact of climate in future without adaptation (Core Question 2).

	C1		C2		C3		C4		C5	
Aggregate results	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Projected mean yield (rice) (kg/ha)	3580	3580	3580	3580	3580	3580	3580	3580	3580	3580
Mean yield change (rice) (%) [defined as: (mean relative yield −1)*100]	−14	2	−23	−20	−9	−4	−12	6	−12	−10
Projected mean yield (wheat) (kg/ha)	5303	5303	5303	5303	5303	5303	5303	5303	5303	5303
Mean yield change (wheat) (%) [defined as: (mean relative yield −1)*100]	−17	6	−29	15	−24	7	−20	6	−24	7
Observed mean yield (livestock) (kg/animal/annum)	1708	1708	1708	1708	1708	1708	1708	1708	1708	1708
mean yield change (livestock) (%)	−10	−10	−10	−10	−10	−10	−10	−10	−10	−10
Losers (%)	55.1	40.8	63.8	47.3	54.8	43.0	54.5	38.7	56.1	45.4
Gains (% mean net returns)	21.0	26.2	18.5	23.8	21.0	25.3	21.3	28.6	20.7	24.4
Losses (% mean net returns)	−23.6	−21.2	−25.4	−22.4	−23.4	−21.5	−23.6	−22.0	−23.8	−22.0
Projected net returns without climate change (Rs./farm)	58977	59161	58931	59062	58973	59115	58983	59356	58968	59084
Projected net returns with climate change (Rs./farm)	56985	63010	53618	60164	57086	62014	57226	64244	56565	60968
Projected *per capita* income without climate change (Rs.)	23614	23660	23603	23636	23613	23649	23616	23709	23612	23641
Projected *per capita* income with climate change (Rs.)	23114	24628	22268	23912	23139	24377	23174	24938	23008	24114
Projected poverty rate without climate change (%)	48.2	48.1	48.2	48.1	48.2	48.1	48.2	48.1	48.2	48.1
Projected poverty rate with climate change (%)	49.3	46.0	51.3	47.6	49.3	46.5	49.2	45.4	49.6	47.1

Note 1: C1–C5 = climate models, C1 = CCSM4, C2 = GFDL-ESM2M, C3 = HadGEM2-ES, C4 = MIROC5, C5 = MPI-ESM-MR; M1 = crop model (APSIM), M2 = crop model (DSSAT).
Note 2: Poverty line for analysis is assumed Rs. 22812.50 *per capita*/annum, which is equivalent to USD1.25 per capita/day. National poverty line is Rs. 11000.
1USD = 55INR.

Core Question 3: What Are the Benefits of Climate Change Adaptations?

Impact of adaptation on crop productivity

Though the TOA-MD analysis brings out negative as well some positive impact of climate change depending on the yield projections made by different crop models (APSIM and DSSAT), a large proportion of the population remains vulnerable to climate change. Therefore, it was tested as to how an adaptation strategy would affect the future agricultural production system. The adaptation strategy tested for the future agricultural production system was to advance the date of sowing of wheat crop by ten days. This strategy was tested because terminal heat (during maturing stage) has severe adverse impact on the wheat yield. It is assumed that the remaining farm enterprises (rice and livestock in this case) remain unaffected by the adaptation strategy. The model simulations for adaptation strategy show an increase in wheat yield ranging from 9 to 13% for APSIM but only 1 to 3% for DSSAT. The results of the adoption of the adaptation strategy are presented in Table 6.

Impact of adaptation on farmers' livelihoods

The adaptation strategy is likely to result in an increase of 15.5–18.6% in mean net farm returns for APSIM but the magnitude of increase would be lower (10–11%) for DSSAT. The *per capita* income would increase by 10–11% and 6–7% for APSIM and DSSAT, respectively. Consequently, the poverty rate would decline by 3–5% for the population as a whole. The adoption rates for the adaptation strategy ranges from 59–64% for APSIM but less than 50% (46–49%) for DSSAT under five GCMs. Overall, the adaptation strategy results in an increase in mean net farm returns for the population as a whole. However, 36–41% of the population still remains vulnerable to climate change. It may be noted that the adaptation is tested for one crop (wheat) only and the yield increases are not substantially higher due to which a substantial proportion of farm population do not adopt the adaptation strategy. Therefore, different adaptation packages and a set of elaborate RAPs visualizing more realistic features of the future agricultural production systems need to be tested to formulate an effective strategy under climate change and for ensuring economic viability and livelihood security of smallholders in the region.

Next Steps

There is a need to include more crops in the integrated assessment, particularly in future systems. For example, sugarcane–wheat is another predominant cropping system in this region. There is also a need to incorporate more soil types and additional

Table 6. Adoption of adaptation package (Core Question 3).

	C1		C2		C3		C4		C5	
Aggregate results	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Projected mean yield (rice) (kg/ha)	3092.5	3626.1	2776.2	2874.6	3282.4	3400.0	3199.4	3782.9	3201.0	3211.4
Mean yield change (rice) (%) [defined as: (mean relative yield −1)*100]	0	0	0	0	0	0	0	0	0	0
Projected mean yield (wheat) (kg/ha)	4364.9	5600.6	3724.1	6106.3	3988.5	5688.1	4225.0	5609.8	3977.8	5686.0
Mean yield change (wheat) (%) [defined as: (mean relative yield −1)*100]	**9**	**3**	**13**	**1**	**10**	**3**	**9**	**3**	**10**	**3**
Projected mean yield (livestock) (kg/animal/annum)	1537	1537	1537	1537	1537	1537	1537	1537	1537	1537
Mean yield change (Livestock) (%) [defined as: (mean relative yield −1)*100]	0	0	0	0	0	0	0	0	0	0
% adoption rate	59.4	49.2	64.6	45.8	61.7	48.7	59.9	49.2	61.8	48.6
Projected net returns without adaptation (Rs./farm)	57175	63061	53986	60172	57351	62058	57439	64277	56843	61004
Projected net returns with adaptation (Rs./farm)	66062	69805	64054	66077	66883	68629	66513	71154	66406	67510
Projected *per capita* income without adaptation (Rs.)	23161	24640	22360	23915	23206	24388	23228	24946	23078	24124
Projected *per capita* income with adaptation (Rs.)	25394	26335	24890	25398	25601	26040	25508	26674	25481	25758
Projected poverty rate without adaptation (%)	49.3	46.0	51.2	47.6	49.2	46.6	49.1	45.4	49.5	47.1
Projected poverty rate with adaptation (%)	44.6	42.5	45.8	44.4	44.2	43.1	44.3	41.9	44.5	43.7

Note 1: C1–C5 = climate models, C1 = CCSM4, C2 = GFDL-ESM2M, C3 = HadGEM2-ES, C4 = MIROC5, C5 = MPI-ESM-MR; M1 = crop model (APSIM), M2 = crop model (DSSAT).
Note 2: Poverty line for analysis is assumed Rs. 22812.50 *per capita*/annum, which is equivalent to USD1.25 per capita/day. National poverty line is Rs. 11000.
1USD = 55INR.

sites for the integrated assessment because of a wide variability in soil characteristics. Since we have not incorporated livestock and other components of the farming system in the integrated assessment, there is a need to incorporate the modeling of these components to achieve more comprehensive integrated assessments. Similarly, a methodological framework should be developed for up-scaling the integrated assessment for the entire IGB.

References

Aggarwal, P. K. and Mall, R. K. (2002). Climate change and rice yields in diverse agro environments of India. II. Effect of uncertainties in scenarios and crop models on impact assessment, *Clim. Change*, **52**, 331–343.

Aggarwal, P. K. and Sinha, S. K. (1993). Effect of probable increase in carbon dioxide and temperature on productivity of wheat in India, *J. Agric. Meteorol.*, **48**, 811–814.

AgMIP (2013). *Guide for running AgMIP climate scenario generation tool with R in windows*, Version 2.0, AgMIP, New York, pp. 1–44.

Ängstrom, A. (1924). Solar and terrestrial radiation, *Quarterly Journal of Royal Meteorological* Society, **50**, 121–126.

Antle, J. M. and Valdivia, R. O. (2012). TOA-MD: New methods to assess climate change impacts and adaptation for poor agricultural households. Available at: http://tradeoffs.oregonstate.edu/sites/default/files/toa-md_poster_cc_10_01_12c.pdf. Accessed on 21 December 2013.

Chaturvedi, R. K., Joshi, J., Jayaraman, M., Bala, G., and Ravindranath, N. H. (2012). Multimodel climate change projections for India under representative concentration pathways (RCPs): A preliminary analysis, *Curr. Sci.*, **103**, 791–802.

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., and Herrero, M. (2012). A method for evaluating climatic change adaptation strategies for small-scale farmers using survey, experimental and modeled data, *Ag. Syst.*, **111**, 85–95.

Goswami, B. N., Venugopal, V., Sengupta, D., Madhusoodanan, M. S., and Xavier, P. K. (2006). Increasing trend of extreme rain events over India in a warming environment, *Science*, **314**, 1442–1445.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasey, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J. (2010). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

IPCC (2007). Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L. (eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC*, Cambridge University Press, Cambridge.

IPCC (2013). Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, p. 1535.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**(3), 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silbum, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCron, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**(3), 267–288.

Krishnamurthy, C. K. B., Lall, U., and Kwon, H. H. (2009). Changing frequency and intensity of rainfall extremes over India from 1951 to 2003, *J. Clim.*, **22**, 4737–4746.

Kulkarni, A. (2012). Weakening of Indian summer monsoon rainfall in warming environment, *Theor. Appl. Climatol.*, **109**(3–4), 447–459.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., Detlef, P., van Vuuren T., Carter, R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., John, F. B., Makicenovic, M. N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

Medugu, D. W. and Yakubu, D. (2011). Estimation of mean monthly global solar radiation in Yola-Nigeria using angstrom model, *Adv. Sci. Res.*, **2**(2), 414–421.

Pathak, H., Ladha, J. K., Aggarwal, P. K., Peng, S., Das, S., Yadvinder-Singh, Bijay-Singh, Kamara, S. K., Mishra, B., Sastri, A. S. R. A. S., Aggarwal, H. P., Das, D. K., and Gupta, R. K., (2003). Climatic potential of on-farm yield trends of rice and wheat in the Indo-Gangetic Plains, *Field Crops Res.*, **80**, 223–234.

Pattanaik, D. R. and Rajeevan, M. (2010). Variability of extreme rainfall events over India during southwest monsoon season, *Meteorol. Appl.*, **17**, 88–104.

Probert, M. E., Dimes, J. P., Keating, B. A., Dalal, R. C., and Strong, W. M. (1998). APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems, *Agric. Syst.,* **56**(1), 1–28.

Rajeevan, M., Bhate, J., and Jaswal, A. K. (2008). Analysis of variability and trends of extreme rainfall events over India using 104 years of gridded daily rainfall data, *Geophys. Res. Lett.*, **35**(18).

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Antle, J. M., Boote, K. J., Thorburn, P., and Valdivia, R. O. (2014). *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.1*. Available at: http://www.agmip.org/wp-content/uploads/2014/07/AgMIP-Regional-Integrated-Assessment-Handbook-v5.1.pdf. Accessed on 21 March 2014.

Rosenzweig, C., Jones, J. W., Hatfield, J. L, Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C, Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Ruane, A. C., Goldberg, R. and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol.*, 200. doi: 10.1016/j.agr.formet.2014.09.016.

Ruane, A.C. and Hudson, N. (2013). *Guide for Running AgMIP Climate Scenario Generation tools with R in windows*, Version 2.0, AgMIP, New York, pp. 1–43.

Sen Roy, S. (2009). A spatial analysis of extreme hourly precipitation patterns in India, *Int. J. Climatol.*, **29**, 345–355.

Subash, N., Shamim, M., Singh, V. K., Gangwar, B., Singh, B., Gaydon, D. S., Roth, C. H., Poulton, P. L., and Sikka, A. K. (2014). Applicability of APSIM to capture the effectiveness of irrigation management decisions in rice-based cropping sequence in the Upper-Gangetic Plains of India, *Paddy and Water Environment*, June.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design, *Bull. Am. Meteorol. Soc.*, **93**(4), 485–498.

Valdivia, R. and Antle, J. M. (2014). "Develop RAPs for use in regional analysis of climate impact and adaptation", in *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures*, Version 5.1, pp. 1–53.

Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P., and Meams, L. O. (2004). *Guidelines for use of climate scenarios developed from statistical downscaling methods*. Available at: www.ipcc-data.org/guidelines/dgm_no2_v1_09_2004.pdf1. Accessed on 21 December 2013.

Chapter 9

Integrated Assessment of Climate Change Impacts on Maize Farms and Farm Household Incomes in South India: A Case Study from Tamil Nadu

Paramasivam Ponnusamy[1], Geethalakshmi Vellingiri[1], Raji Reddy Danda[2], Lakshmanan Arunachalam[1], Dakshina Murthy[3], Sunandini Prema[2], Sreenivas Gade[2], Sonali P. McDermid[4], and Roberto O. Valdivia[5]

[1]*Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India*

[2]*Acharya N. G. Ranga Agricultural University, Hyderabad, Telangana, India*

[3]*International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad, Telangana, India*

[4]*New York University, New York, NY, USA*

[5]*Oregon State University, Corvallis, OR, USA*

Introduction

South India is characterized by a wide variety of landscapes, soils and climatic zones. It is comprised of tropical, semi-arid, humid–moist, and high-altitude environments, which support a diversity of agricultural systems. Our study focuses on the state of Tamil Nadu, which is characterized by a generally tropical climate, and receives rainfall during both the southwest monsoon season (SWM, June to September) and the northeast monsoon (NEM, September to December).

Tamil Nadu has a 960-km coastline along the southernmost tip of the Indian Peninsula between 8°5' N and 13°35' N and 76°15' E and 80°20' E. Seven percent of the India's population inhabits the state, which encompasses 4% of the land area and 3% of the water resources. Due to its proximity to the sea, Tamil Nadu experiences relatively high temperatures and humidity throughout the year. Summer

is experienced from April through June (with the temperature rising up to 40°C), and winter from November through February (with temperatures averaging 20°C). Tamil Nadu gets the major share of its rains from the NEM (48%), followed by the SWM (32%), and greater summer (15%) seasons. The average annual state-wide rainfall ranges from 535 to 2905 mm/year, with a state average annual rainfall of 945 mm.

Tamil Nadu encompasses an area of 130,058 km^2, which includes 22,934 $km^2$of forest. The state has been divided into five major physiographic divisions, *viz.*, mountainous region, forest region, arid region, fertile plains, and coastal region. The Eastern and Western Ghats meet in this state and run along its east and west borders. Tamil Nadu has 3.03 million ha of cultivable land (∼43% of geographical area), of which 42% is rainfed and 58% is irrigated (Department of Economics and Statistics, Tamil Nadu, 2010). Major crops grown in the state are rice, maize, sorghum, pulses, oil seeds, cotton, sugarcane, minor millets, vegetables, fruits and other horticultural crops.

Agriculture continues to be an important sector in the state economy, as more than 56% of the people depend on agriculture and allied sectors for their livelihood. Analysis of land-use patterns in Tamil Nadu reveals that in the past decade there has been a reduction in net sown area and current fallow, while the share of cultivable wastelands has increased. The area under cereals, pulses, and oilseeds had marginally declined, although area under commercial crops like turmeric, sugarcane, banana, fruits, and vegetables has shown an increasing trend. The production performance of major crops like cereals, pulses, and oilseeds has not shown any significant increase. Demand and supply gap of important crops in Tamil Nadu for the year 2010 (estimated by the State Planning Commission (Srivastava *et al*., 2010)), indicates that the state is lagging far behind in the production of various crops.

Sixty-five percent of the Tamil Nadu's population resides in rural areas. According to National Sample Survey Organization data (1999–2000), out of the total population of 62 million in Tamil Nadu, about 12 to 17 million people are living below the poverty line. As per the poverty estimate of Rural Development Department of Government of Tamil Nadu, the overall poverty ratio stood at 22.8% in 2004 (Srivastava *et al*., 2010).

Climate change challenges

The monsoonal rains display a large amount of internal variability and also exhibit variation with external climatic forcings, such as the El Niño Southern Oscillation (Turner and Annamalai, 2012) and the Madden–Julian Oscillation (Turner and Annamalai, 2012). In addition, there is much concern about how this already-variable system might change with climate change, and how the latter might impact coastal

agricultural communities and fisheries, which are subject to extreme storms and weather events. Regional projections suggest increased temperatures, along with increased rainfall, although much uncertainty exists in how the system's variability will change (Turner and Annamalai, 2012). Much of the region's agriculture is rainfed, and the timing of the monsoon rains is important to achieving optimal crop growth, so understanding how climate change may impact the system is critical to future agricultural planning and management. Indeed, those irrigated systems that rely on surfacewater stores are also indirectly dependent upon the monsoon rains, which supply these stores and contribute recharge to other water supplies. Water availability and use efficiency are also limited in part by fluctuations in temperature, which are further subject to change under warmer climate conditions (Mall *et al.*, 2006).

Maize-based farming system in Coimbatore, Tamil Nadu

Coimbatore is positioned at 11° N latitude and 77° E longitude with mean altitude of 426.7 m MSL. Being in the rain shadow area of Western Ghats, its climate is arid during winter (January to February), summer (March to May), and SWM (June to September) seasons. During the NEM the climate is dry subhumid as per Thornthwaite and Mather's (1955) classification. Coimbatore's annual climate is classified as semi-arid.

In Tamil Nadu, maize accounts for 83.4% (200,000 ha) of the total area. It is mainly cultivated in Perambalur, Dindigul, Coimbatore, Salem, Erode, and Virudhunagar Districts, which together share 77.1% of the total area under this crop in the state. Farmers in Tamil Nadu, who in recent years were affected by price volatility in sugarcane, turmeric, and vegetables, are now switching over to maize cultivation. Immediate liquidity in the market, store-and-sell facilities, and high demand from the poultry industry has also prompted Tamil Nadu farmers to increase the area under maize cultivation.

In Coimbatore, vegetables, maize, and groundnut are grown under garden land conditions, whereas maize, sorghum, groundnut, small millets, and pulses are grown as rainfed crops in red soils. Cotton, sorghum, bengal gram, and sunflower are raised in black soils. Farm household work, agriculture and livestock activities are complementary on a day-to-day basis. The predominant maize-based cropping systems followed in Coimbatore are, maize–sunflower/tomato, maize/maize-cotton/pulse, maize/maize, groundnut. Livestock, such as goats, cows, and poultry, are also major components in the farming systems as they play a significant role in regular employment and income generation. These activities increase the total farm income, and act as an alternative livelihood source in the event of crop failure (due to extreme weather conditions or otherwise).

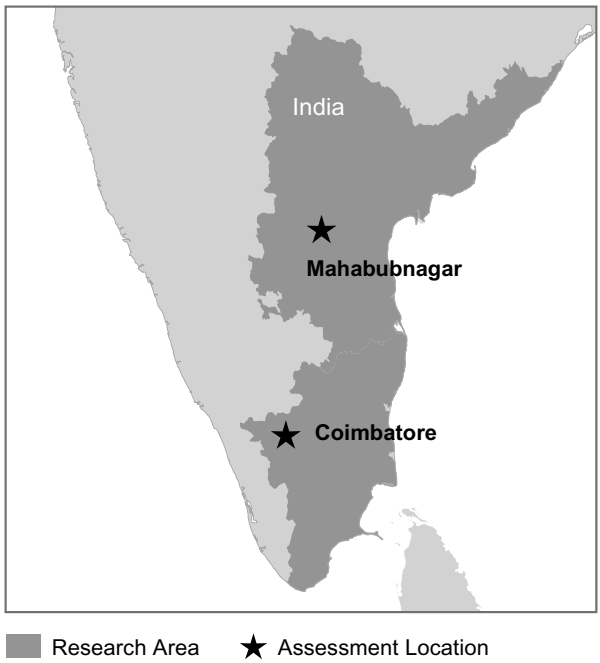


Fig. 1. AgMIP South India region, and study districts in Coimbatore, Tamil Nadu, and Mahabubnagar, Andhra Pradesh.

Representative Agricultural Pathways: Development and Interactions with Stakeholders

Climate change is now widely accepted as a significant long-term environmental challenge. Global climate and economic modelers have been developing likely scenarios of how nations might follow economic growth paths. Examples of such paths or trajectories include the representative concentration pathways (RCPs) of carbon emissions, used to inform climate model simulations, and the shared socio-economic pathways (SSPs) that describe likely future trends in biophysical and economic variables (Kriegler *et al.*, 2012; Van Vuuren *et al.*, 2011). While global SSPs may give general global projections, it is desirable to use them as guidelines to derive regional future outcomes of non-climate variables and describe them as regional SSPs. When this exercise is carried out to represent the future regional agriculture sector, they are termed regional representative agricultural pathways (RAPs). Since RAPs are statements about the likely evolution of variables like soil fertility, farm size, and regulatory policies, their development needs inputs from informed stakeholders to make them more reliable. The process of building regional RAPs is guided by the global SSPs. SSPs provide an overall future socio-economic scenario

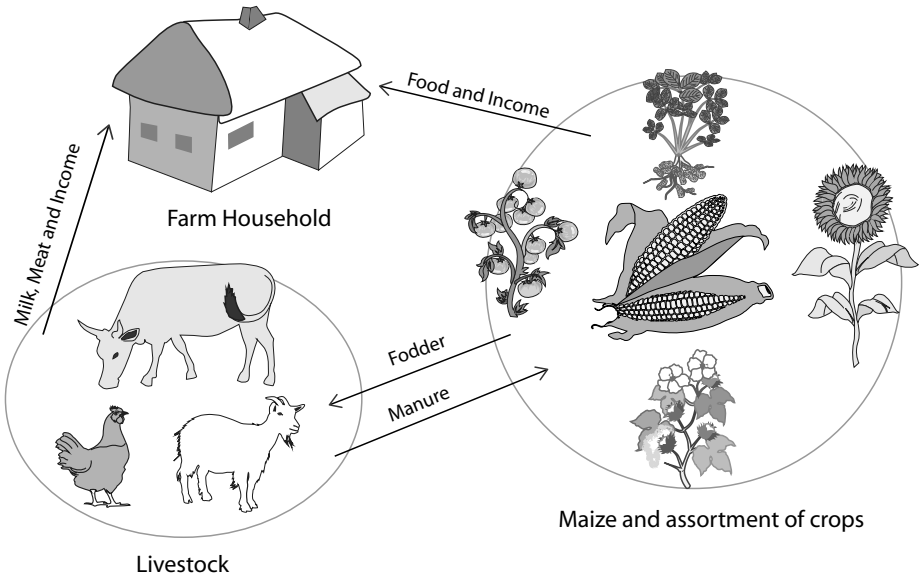


Fig. 2. Typical maize-based farming system in South India.

for the world's regions, which in turn assumes varying degrees of challenges to mitigation and adaptation strategies to climate change. SSPs and sector-specific global, national, and subnational trends guide the formulation of the regional RAPs (see Part 1, Chapter 5 in this volume).

In order to formulate these RAPs to be representative of the regional potential agricultural and socio-economic development, we sought to engage a range of stakeholders at the local, municipal, and state levels. Such a participative approach helps to characterize and integrate futuristic socio-economic productions systems with climate change impact assessment better (Berkhout *et al*., 2002). A RAPs workshop was held on February 22, 2013 at the Department of Agricultural Economics at Tamil Nadu Agricultural University (TNAU) in Coimbatore. A brief presentation was made by the project team about the process of building RAPs so as to facilitate deeper understanding of the process and a fruitful discussion ensued. For each variable, e.g., soil quality in a particular region, the research team presented a literature-based assessment and stakeholders deliberated on how it will evolve until the end of this century. They discussed and came to a consensus on the direction of change (e.g., soil quality will decline), magnitude of change (high/medium/low), rationale for the direction and magnitude of change, specific quantitative value of change (e.g., 5% or 10%), the rationale for this particular value, and the level of agreement among the group as a whole with regard to this particular change.

A second and wider RAPs workshop that incorporated policymakers from government departments including the Planning Commission and the Department of Environment was organized on 18/19 July, 2013 by the Departments of Agricultural Economics and Agro-Climatic Research Centre at TNAU. The results of the earlier RAPs workshop and conclusions were presented to the group. The participants (the team of project scientists and the domain experts from various institutions from Tamil Nadu) deliberated on the results presented and, through intergroup discussions, arrived at a final consensus on how the socio-economic and biophysical variables pertaining to agriculture and rural development will evolve in the course of the present century.

Data and Methods of Study

The Agricultural Model Intercomparison and Improvement Project (AgMIP) integrated assessment of climate change impacts (Rosenzweig *et al.*, 2013) on agricultural production involves four components in the modeling process: Characterization of the agricultural production system, modeling climate change, simulating crop yields with crop models, and understanding how yield changes may impact the farm populations' livelihood and poverty levels. Production systems comprise crop, livestock, and other farm activities. Major crops around which the production systems are organized are identified. Calibrated and validated models for these crops are used to simulate yields under varying climate projections from climate models and management inputs derived from farm surveys. Finally adaptation options (included as part of RAPs discussions) are incorporated in crop model runs to evaluate their efficacy. The resulting yield data are used to compute crop incomes, and when combined other farm activities, can be used to compute the whole farm income. We can thus assess farm incomes for a combination of current and future production systems, with respective climate conditions and adaptation options.

Using the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD; Antle, 2011), we can understand questions related to climate change and its impacts and the production systems better. In particular AgMIP tries to address three important issues: (1) the sensitivity of current agricultural production systems to climate change (i.e., how will the current system respond if the future climate is to be experienced now?); (2) impact of climate change on future agricultural production systems (i.e., defined by the agricultural production system as it would exist in the future and evaluate the impact of climate change); (3) the efficacy of on-farm adaptations in alleviating the impact of climate change. Three major assumptions are made to characterize the future production system, which include: There will be technological trends that will result in increased crop yields, economic trends

unrelated to climate change (as predicted by global economic models), and changes in produce prices due to global demand supply changes.

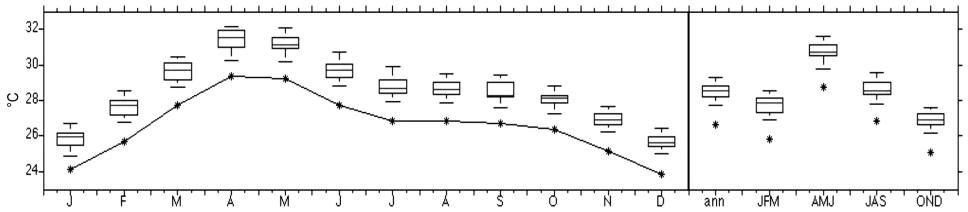
Climate data and scenarios

Baseline climate data

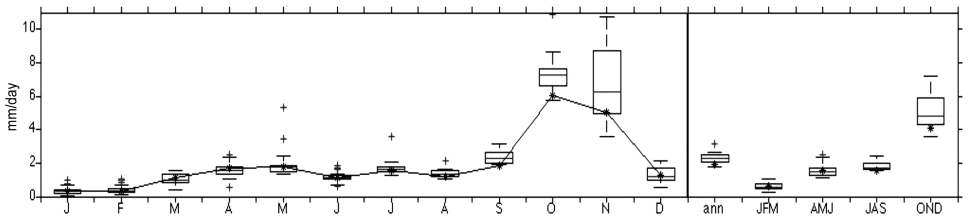
The study site lies in Coimbatore, which is situated in northwest Tamil Nadu, covering an area of 4889 km^2. Within Coimbatore, the analysis was focused in the Coimbatore block, which receives its maximum rainfall during the NEM season (373 mm), followed by SWM season (183 mm). The annual rainfall received is estimated to be 714 mm. The coefficients of variation (CV) are 35% and 37% for NEM and SWM rainfall, respectively. The annual average maximum and minimum temperatures in the study region are 31.8 and 21.5°C, respectively. Thirty years (1980–2010) of observed daily weather series was obtained from TNAU's Agromet observatory, located at 11° N latitude and 77° E longitude. The baseline weather datasets were quality controlled and inspected for outliers or anomalous values; if found, such values were adjusted and corrected with the AgMIP-provided AgMERRA reanalysis dataset (Ruane *et al*., 2014). In order to create a representative 30-year weather series for each farm, we utilized neighboring sites from the highly spatially resolved WorldClim data (Hijmanss *et al*., 2005), which is available historically as monthly values. These monthly values were used to bias-correct the existing 1980–2010 weather series for a tailored fit to each of the farm sites.

Climate projections

Projections of future climate were obtained by using the most recent Coupled Model Intercomparison Project (CMIP5) (Taylor *et al.*, 2012) and the RCPs (Moss *et al*., 2010) for carbon emissions currently in use by the IPCC Fifth Assessment Report. Future climate projections were created by utilizing a "delta" approach, in which the mean monthly changes in important agroclimatic variables were calculated by taking the difference between the RCP8.5 climate scenario and baseline conditions. Scenarios were generated for the near term (centered around 2030), the mid-century (centered around 2055), and the end of century (centered around 2080). These monthly mean agroclimatic changes, or deltas, were then applied to the daily baseline weather series for each month. The future climate series and the corresponding projected carbon dioxide concentration from RCP8.5 were used in all crop model simulations. We refer to these future projections as "mean change scenarios". This procedure was repeated for 20 of the CMIP5 global climate models (GCMs). For the crop model and agroeconomic analyses presented in this chapter, five GCMs were selected that each represented climatic processes important in simulating the SWM and were



(a) RCP8.5 mid-century temperature secenarios for all GCMs (Coimbatore, India)



(b) RCP8.5 mid-century precipitation secenarios for all GCMs (Coimbatore, India)

Fig. 3. Projected changes in monthly mean (a) temperature and (b) rainfall for RCP8.5 mid-century in Coimbatore. Black lines and stars indicate the baseline climate and the box-and-whisker plots show the spread in projections amongst the 20 GCMs taken from CMIP5. Averages for the annual (ann), January to March (JFM), April to June (AMJ), July to September (JAS), and October to December (OND) are shown at the far right of each plot.

shown to adequately reproduce the regional South Asian climate. These models include CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-EMS-MR, and their selection is discussed in greater detail in Part 1, Chapter 3 in this volume.

Based on these mean change scenarios, GCMs generally showed increase in NEM rainfall in Coimbatore (Fig. 3b) although GCM typically have difficulty in simulating NEM rainfall with course resolution. However, some of the 20 GCMs also indicated declines in rainfall, and so uncertainty exists in this projection. The uncertainty is more during NEM as this season is dominated by cyclonic storm activity which might not be captured by all the models employed for NEM prediction. Rainfall during the SWM is not shown to increase substantially in Coimbatore. The GCMs do largely agree that Coimbatore will experience a significant warming throughout the year (Fig. 3a). However, there is a 2–3°C spread between the projected increases, with MIROC5 showing the smallest increase in temperature, and the HadGEM2-ES shows the greatest warming (Fig. 4). Furthermore, minimum temperature (not shown) is also projected by all the GCMs to increase, and the magnitude of increase in minimum temperature was considerably higher than the maximum temperature.

Figure 4 shows the spread of the 20 GCMs in projected temperature and rainfall over the SWM season (June to September), indicating the change from the baseline. All models show a warming, while the precipitation response is decidedly more

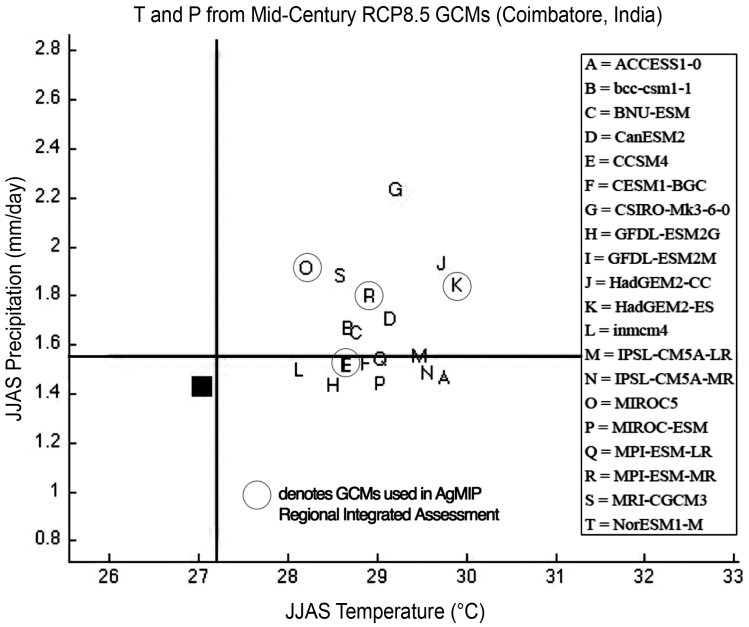


Fig. 4. Projections for SWM (June to September) rainfall and mean temperatures under RCP8.5 mid-century climate conditions in Coimbatore. Black lines indicate calculated significance thresholds (at the 0.05 level), beyond which the temperature and rainfall changes become significant. The black square indicates the baseline temperature and seasonal mean rainfall. Please refer to Part 1, Chapter 3 in this volume for more details on statistical significance testing.

uncertain. The intersecting black lines indicate the threshold of change considered significant (at the 0.05 level) for temperature and rainfall. While all temperature changes are significant, several GCMs show insignificant precipitation changes, although three of the five selected GCMs show a strongly (positive) significant rainfall response change.

Crop modeling

Crop model input data

Dynamic crop system models serve as decision supporting tools, and have been extensively utilized by agricultural scientists to evaluate the consequences from interannual climate variability and/or climate change (Challinor and Wheeler, 2008; Semenov and Doblas-Reyes 2007). Crop simulation models require quality data on climate, soil profiles, crop varieties, crop management details, etc. Efforts were made to collect long-term quality data of the study region from different sources including TNAU, a farmer survey, Department of Agriculture, and scientific experts. The details of the above parameters are discussed below.

Weather data

The weather input dataset of the DSSAT (Decision Support System for Agrotechnology Transfer) model requires the daily sum of radiation (MJ/$m^{2/}$day), the daily minimum and maximum air temperatures (°C), the daily precipitation (mm), windspeed (m/s), dewpoint temperature (°C), vapor pressure, and relative humidity (%). These daily weather data including site-specific information were collected from high-quality observational station data. The station data was used to create tailored weather series for all 60 farms through a bias-correction by using WorldClim monthly weather information and AgMIP climate methodologies (Part 1, Chapter 3 in this volume). These weather series were then used for creating the appropriate weather files for use with the DSSAT-maize model.

Soil information

The soil inputs describe the physical, chemical, and morphological properties of the soil surface and each soil layer within the root zone. The soil samples were collected from opened-up soil profile, and the soil physical and chemical characteristics described layer wise. The same data was used for creating the soil file (RJNR.SOL), required for running CERES-maize model. The Coimbatore district has two major soils, *viz.*, clay and sandy loam. Clay soils had a depth of up to 138 cm with drainage lower and upper limit of 0.24 and 0.44 cm^3/cm^3, bulk density of 1.14 to 1.25 g/cm^3, cation exchange capacity of 21.6 to 26.2 cmol/kgand soil organic carbon ranging from 0.48% to 0.83% in different layers. Sandy soils had depths up to 52 cm with drainage lower and upper limits of 0.13 and 0.25 cm^3/cm^3, cation exchange capacity of 9.2 to 15.9 cmol/kg, and soil organic carbon ranging from 0.48% to 0.6% in different layers.

Genetic coefficients

Plant parameters and physiological characteristics are given in the form of genotype coefficients, which describe physiological processes such as development, photosynthesis and growth for individual crop varieties. In the CERES-maize model of DSSAT, the genetic coefficients for maize are P1 (thermal time from seedling emergence to the end of the juvenile phase), P2 (extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours)), P5 (thermal time from silking to physiological maturity), G2 (maximum possible number of kernels per plant), G3 (kernel filling rate), and PHINT (Phylochron interval).

In the APSIM (Agricultural Production Systems Simulator) model, the coefficients calibrated for simulating maize yield include thermal times for emergence to

end of juvenile (tt_emerg_to_endjuv), flowering to maturity (tt_flower_to_maturity), flowering to start of grain (tt_flower_to_start_grain units), maximum number of grains per head (head_grain_no_max in numbers), and grain growth rate (grain_gth_rate in mg/grain/day).

Crop management data

Crop management parameters used in setting up simulations for individual farms were derived from the results of the socio-economic survey conducted in the study region. The survey captured the details on variety used, date planted, planting geometry, and fertilizer applied, etc., during the SWM season. Farmers in the study region cultivated mainly maize cultivars COH3 and COH(M)5. The crop model was calibrated for these cultivars by using the field data from experiment conducted at TNAU. Survey reports showed that the plant population normally adapted by farmers in the region varied from 60,000 to 80,000 plants/ha as per the plant geometry followed by different farmers. Survey results indicated large differences in the amount of fertilizer used by farmers. Out of 60 farmers, three had used less than 150 kg of nitrogen/ha, 30 farmers used 150–200 kg of nitrogen/ha, and 27 farmers used more than 200 kg of nitrogen/ha. While setting up of the model for individual farmers, we used the actual amounts of nitrogen fertilizer applied by them. All the farmers applied nitrogen in the form of urea via three splits, *viz.*, 25% at basal, 50% at 30 days after sowing, and 25% at flowering stage.

Model calibration

Crop simulation models APSIM and DSSAT were calibrated for maize cultivars COH3 and COH(M)5 in the study region by using the field data from experiments carried out at TNAU, Coimbatore. Date collected from six dates of sowing experiments (15.09.2000, 11.10.2000, 30.10.2000, 11.07.2001, 24.07.2001, 24.08.2001) for maize cultivar COH3 and six dates of sowing experiments (15.07.2009, 30.07.2009, 15.08.2009, 15.07.2010, 30.07.2010, 15.08.2010) for maize cultivar COH(M)5 were used for calibration of crop simulation models.

Input details required by crop simulation models (DSSAT and APSIM) including site information, soil properties, initial conditions, planting time, irrigation management (dates, amounts, and schedule), and fertilizer management (dates, amounts, sources, method of incorporation, and depth of placement) were obtained from the field experiments. The daily weather data on solar radiation, maximum and minimum air temperatures, and rainfall were collected from the TNAU observatory. CERES-maize (DSSAT) and APSIM models were calibrated by comparing simulated outcomes with the available measured data on days to tasseling, flowering, maturity, and grain yield at harvest.

The genetic coefficients that influence the occurrence of developmental stages in the crop model were derived iteratively, by manipulating the relevant coefficients to achieve the best possible match between the simulated and observed number of days to the phenological events and grain yield. Simulations with final set of parameters by both the models indicated good relationship between observed and simulated days to flowering, days to maturity, and yield (Fig. 5).

The calibrated genetic parameters of maize cultivars used in the DSSAT model are given in Table 1a. The calibrated genetic parameters of maize cultivars used in the APSIM model are given in Table 1b. The calibration efficiency has been tested by the statistical measures such as root-mean-square error (RMSE) and coefficient of determination (R^2) and the results are presented in Table 2.

The model statistics of DSSAT for COH(M)5 indicated that the R^2 values are 0.82, 0.84, and 0.85 for days to anthesis, physiological maturity, and yield, respectively, which indicate good agreement between observed and model simulated data. RMSE values for phenological stages are found to be between 2.04% and 2.12%, which indicates a good match between simulated and observed values. The RMSE for yield is found to be within the acceptable limit (351). For COH3, the R^2 value is 0.80, 0.71 and 0.73 for days to anthesis, physiological maturity, and yield, respectively, which indicates a high degree of colinearity between simulated and observed data. RMSE is less for days to anthesis and maturity (1.35 and 2.83) and yield (490), which indicates the good predicting power of the DSSAT model.

The results of the APSIM calibration for COH3 gave high R^2 values (0.65, 0.56, and 0.66 for days to anthesis, physiological maturity, and yield, respectively) and low RMSE values (2.27, 3.58, and 439 for days to anthesis, physiological maturity, and yield, respectively), which indicates good agreement between observed and simulated values. Similar results were obtained for the maize COHM5 cultivar also. The calibration efficiency was tested by using statistical measures such as RMSE and coefficient of determination (R^2) and the results are presented in Table 3.

Crop model results: Baseline analysis and future climate change impacts

Crop growth models are physiologically based, in that they calculate the relationship between various plant functions and environment. The model simulates crop behavior by predicting the growth parameters, such as biomass portioning to leaves, roots, stems, and grains. Thus, a crop growth simulation model not only predicts the final state of total biomass or harvestable yield, but also contains quantitative information

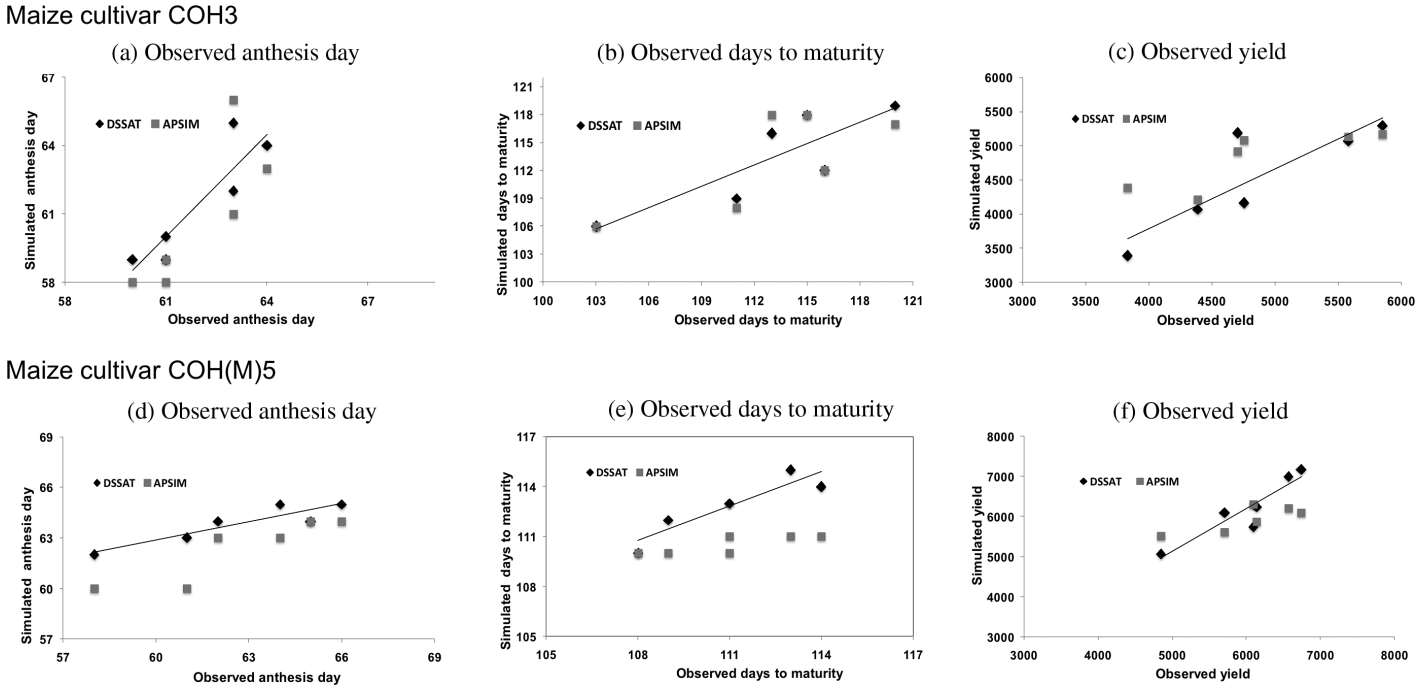


Fig. 5. (a–c) DSSAT cultivar COH3 and (d–f) APSIM cultivar COH(M)5 model predictions of days to flowering, maturity, and yield, respectively.

Table 1a. Genetic coefficients for cultivars of maize in CERES-Maize model.

Cultivar	P1	P2	P5	G2	G3	PHINT
COH3	310	0.530	900	600	7.90	38.3
COH(M)5	330	0.520	860	769	8.50	38.8

Table 1b. Genetic coefficients for maize cultivars in APSIM model.

Cultivar	tt_emerg_ to_end juv	tt_flower_ to_maturity	tt_flower_to_ start_grain units	head_grain_ no_max	grain_ gth_rate
COH3	330	845	117	793	4.6
COH(M)5	450	910	100	510	6.5

Table 2. Model statistics.

		Days to anthesis		Days to maturity		Grain yield	
Model	Model stat.	COH 3	COH(M)5	COH 3	COH(M)5	COH 3	COH(M)5
DSSAT	R^2	0.80	0.82	0.71	0.84	0.73	0.85
	RMSE	1.35	2.12	2.83	2.04	490	351
APSIM	R^2	0.65	0.81	0.56	0.64	0.66	0.64
	RMSE	2.27	1.41	3.58	1.78	439	430

Table 3. Model statistics.

Model	Model stat.	Days to anthesis	Days to maturity	Grain yield
DSSAT	R^2	0.95	0.85	348
	RMSE	0.5	0.86	0.84
	Wilmot d index	0.96	0.87	0.90
APSIM	R^2	1.1	0.4	0.93
	RMSE	0.60	1.93	277
	Wilmot d index	0.78	0.53	0.94

about major processes involved in the growth and development of a plant (Jame and Cutforth, 1996). Crop models have been used extensively to study the impact of climate change on agricultural production and food security (Hoogenboom *et al.*, 2012).

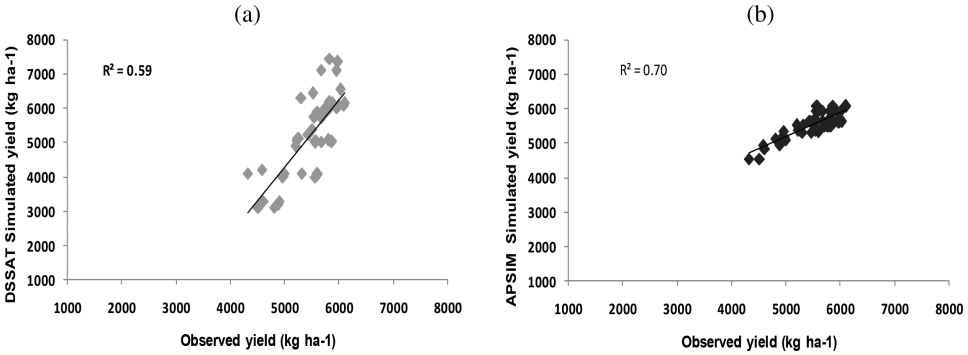


Fig. 6. Relationship between DSSAT and APSIM simulated farmers' yields and reported yields of 2010–2011 cropping season.

Calibrated DSSAT and APSIM models were forced with the survey-year weather data (2010–2011) for the 60 farmers using inputs from the farm socio-economic survey such as variety used, date planted, plant geometry, and fertilizer applied. Crop simulation model setup for the 60 farmers was done using AgMIP tools (e.g. QUAD UI). DSSAT and APSIM simulated maize crop yields for the survey year (2010–2011) were compared with the actual observed yield, and the results are depicted in Fig. 6.

Reported irrigated maize yields varied from 4317 to 6105 kg/ha during the SWM in Coimbatore. A strong correlation between simulated and reported maize yields was observed in the study region. Calibrated DSSAT and APSIM models were then forced with the historical baseline weather data (1980–2010) for 60 farmers, by taking inputs from farm socio-economic survey for the management options. The simulated grain yield is presented in Fig. 7. The results showed that there is heterogeneity among the farms baseline yield, which can be attributed to differences in sowing date, variety, amount of fertilizer applied, soil type, and other crop management practices.

DSSAT and APSIM models were then forced with future projected climate change scenarios of RCP8.5 mid-century generated from selected five GCMs for the same 60 farmers by keeping all the other model parameters constant (variety, soil, management practices, sowing time, and population) to simulate the impact of future climate on the grain yield of irrigated maize (Fig. 8).

Both DSSAT and APSIM model simulations under RCP 8.5 climate conditions (without adaptation) predicted the possibility of yield decline with varying magnitude. DSSAT simulations indicated a differential response of irrigated maize productivity to the future climate generated by different GCMs. Forcing CCSM4, MIROC5, and MPI-ESM-MR models with DSSAT showed a positive deviation in the productivity of maize by 2.33%, 22.22%, and 10.09%, respectively, while

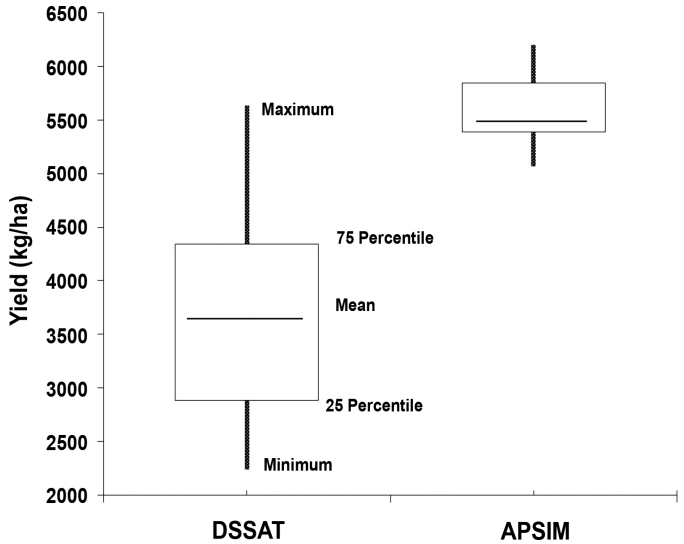


Fig. 7. Baseline DSSAT and APSIM simulated farmers' irrigated maize yields for 60 farmers in Coimbatore, India.

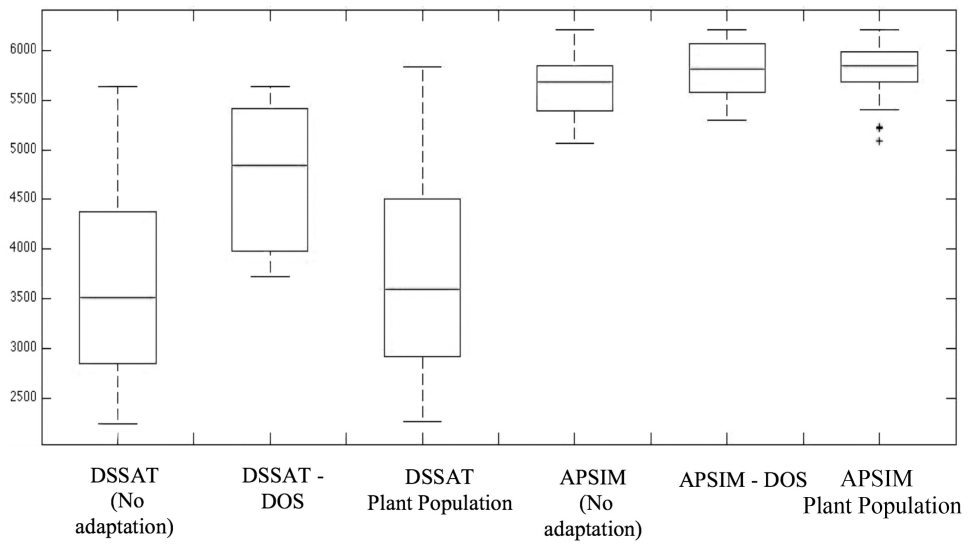


Fig. 8. Projected APSIM and DSSAT simulated maize yields for the future climate scenarios with different sowing dates (DOS) and plant populations.

GFDL-ESM2M and HadGEM2-ES model forcing projected negative deviation (–5.59% and –10.20%, respectively). In contrast, with the APSIM model, all GCM forcing projected negative deviation in irrigated maize yield ranging from –8.75% to –25.36 %. The maximum decline in yield was projected by HadGEM2-ES. DSSAT

simulation showed both positive and negative impact of climate change on maize productivity. However, the DSSAT simulated negative impact was lesser than the APSIM model as the DSSAT had more positive response for the enhanced CO_2 level in the future than APSIM. DSSAT simulation showed both positive and negative impact of climate change on maize productivity. However, the DSSAT simulated negative impact was lesser than the APSIM model as the DSSAT had more positive response for the enhanced CO_2 level in the future than APSIM.

Agroeconomic assessment

Farm survey data

Maize crop is grown under both irrigated and rainfed conditions in Coimbatore, though few maize cropped areas are purely rainfed. Maize cropped areas irrigated with groundwater are known as garden lands. Many farms that do not have surface irrigation sources drill bore wells to irrigate part of their farm holdings. The difference between rainfed maize and irrigated maize is determined by the nature of sowing. Where rainfall determines sowing the area is classified as rainfed, and where groundwater is used for sowing it is irrigated. Sometimes farmers also use "lifesaving" irrigations even if the crop is sown as rainfed.

Most farms grow some combinations of fodder sorghum, vegetables like tomato, brinjal, bhendi, groundnut, and pulses as irrigated or dry crops. Most of the farms raise an assortment of livestock including chicken, goat, sheep, buffaloes and cows, which augment farm income. Buffalos and cows are reared for milk income and goat, sheep and chicken for meat. Crop and livestock activities complement each other.

To assess and develop the variables required to undertake the integrated assessment, data collected from the ongoing Government of India Scheme on cost of cultivation of principal crops in Tamil Nadu were utilized. The data collection, organization and coding is done at the Department of Agricultural Economics, Tamil Nadu Agricultural University from where the data was obtained. Data used relate to 60 farm households that grow irrigated maize along with other crops and livestock. Maize farms are concentrated in the Tiruppur region. Summary statistics related to important variables are presented in Table 4.

Most of the households are nuclear in nature with a family size of around four. Farm sizes are also small with a holding of about 1.85 ha. Maize, other crops and livestock have each contributed almost one third of the household incomes, which indicates the relevance of interdependence. Other crops' net income, however, exhibited comparatively higher variability across farms due to the nature of crops grown and water endowments. Since there is an assortment of other crops not uniformly grown across all farms (and likewise is the case with livestock) their returns and the

Table 4. Farm survey data summary statistics.

	Irrigated maize farms		
Variables	Mean	SD	CV
Household size	4.38	1.08	24.52
Farm size	1.85	1.57	34.34
Maize area (ha)	1.00	0.30	30.16
Yld/ha	7039	996.82	14.16
Maize price/kg	10.73	1.08	10.10
Maize: gross income (Rs)	74918	24987	33.35
Maize: variable cost (Rs)	30447	8215	26.98
Maize: net income (Rs)	44471	18168	40.85
Other crops: gross (Rs)	55642	54859	98.59
Other crops: cost (Rs)	27240	30553	112.16
Other crops: net (Rs)	32152	27608	97.21
Livestock: gross (Rs)	69659	62615	89.89
Livestock: cost (Rs)	30805	62618	203.27
Livestock: net (Rs)	38854	15385	39.60
Non-farm income(Rs)	32778	24351	74.29
Gross farm income (Rs)	232996	80243	40.08
Gross cost (Rs)	88492	68006	76.85
Net farm income (Rs)	144504	35216	31.52

variable production costs associated with them are combined in monetary terms for further analytical purposes.

For this integrated assessment, maize-based farm systems under both the irrigated and rainfed systems were considered. Crop models APSIM and DSSAT were used along with management inputs from survey data to simulate yields under RCPs 4.5 and 8.5, for near, mid- and end-of-century time-periods and climate projections based on CCSM4, GFDL-ESM2M, HadGEM-2-ES, MIROC5, and MPI-ESM-MR GCMs. Simulated yields were used to calculate the current and future system parameters for economic simulations. Results for the core questions based on mid-century yield simulations are presented in subsequent sections.

RAP narrative

There will be a small increase in crop diversity due to the need to combat climate and market risks, because both of these might become more volatile in the future. Water quality and water availability for agriculture will decrease due to pollution of water bodies and competition for water from other sources. On the other hand, water use efficiency in agriculture will increase due to technological progress. Soil quality will decline by a small-to-medium extent, due to pollution and intensive cultivation caused by shrinking land base for agriculture. Most subsidies are likely

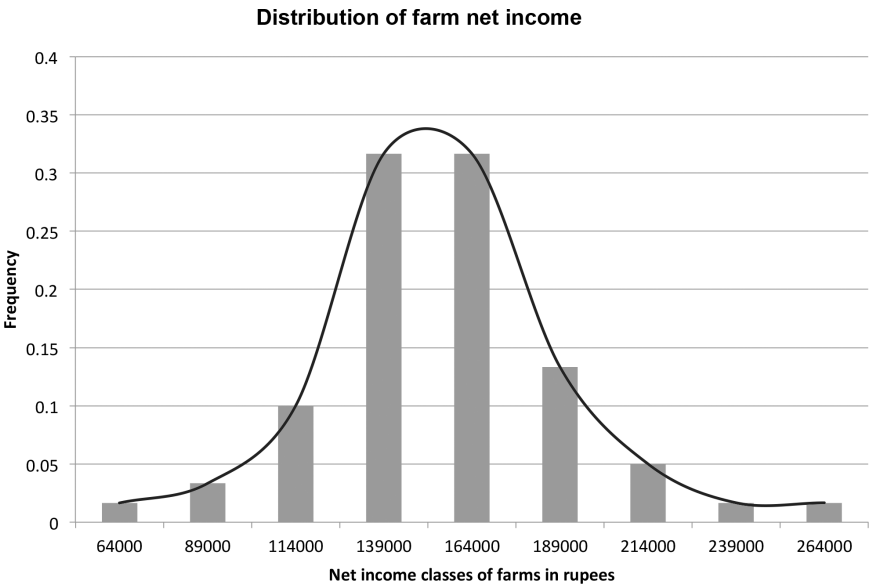


Fig. 9. Farm net income distribution for current irrigated maize production system.

to decline, while prices of agricultural commodities will increase. Farm size and wage rates will increase. Mechanization and energy use intensity will increase. The share of agriculture in overall economy will decrease, while inequality will increase. Significant decline in poverty will be associated with decrease in family size and increase in non-farm income. There will not be significant changes in food imports, while yields of important crops will increase due to technological progress in agriculture. Fertilizer use intensity and fertilizer productivity will increase. The corporate role in agriculture will increase with expanded effectiveness of commodity groups.

While the general regional RAPs cover a wide spectrum of anticipated changes of the agricultural sector in Tamil Nadu, the general consensus was that there will be shortages of land, labor, and water resources available to the sector. In particular, water is found to be the most limiting factor, followed by labor. Capital may have to substitute these factors in the form of improved technology. Thus, some of the major adaptation options identified for coping with both climate change and evolving socio-economic trends include identifying waste management techniques, improvements in land productivity by nutrient management, and improvements in cropping practices.

Tamil Nadu RAP key points include:

- Shrinking land base for agriculture
- Increased farm size and labor costs

- Increased yields of important crops
- Decreased water quality and availability
- Increased water use efficiency — technological progress
- Decline in soil quality
- Fertilizer use and fertilizer productivity increase
- Mechanization and energy use increase
- Increased commodities prices
- Decrease in subsidies
- Climate and market risks

Adaptation package

Adaptation methods enable individuals or communities to cope with or adjust to the impacts of climate change, and take advantage of potential opportunities that may result. Such strategies will include the adoption of efficient environmental-resources-management practices (e.g. the selection of a suitable planting date).

In constructing an adaptation package, it is useful to visualize the different components of the system likely to be impacted. The components of the adaptation package components can be simulated through crop models, or projected based on discussions with experts and literature review, and implemented through the TOA-MD. The process of developing RAPs further informed the adaptation package. Water shortages are envisaged to be a major limiting factor for future agriculture. The study region is partly dependent on groundwater for crop production; its shortage will be felt more and more in the future along with climate impacts. In light of this, the adaptation package envisaged includes altered sowing dates and the use of water-saving measures through drip irrigation, which does not affect the quantum of water normally available to a maize crop. Water saved is expected to be used for other crops and improving yield of fodder sorghum, which can contribute to increased returns from other crops and livestock.

Maize yield impacts due to changes in the date of sowing (DOS) component of the adaptation package were simulated by using the crop models. Other components of the adaptation package along with simulated maize yields were incorporated into TOA-MD for whole-farm analysis. Water-saving measures may involve an additional amortized cost (of an investment of about Rs. 100,000 at 8% interest for a water-saving system with a life-span of about five years) of Rs. 25,000 per hectare per year for the maize crop. This cost is included as a variable cost of maize along with area under maize crop in calculating per farm maize income contribution to the system income. Part of the saved water may be utilized for other crops, which would increase returns from other crop activities by 10%. Improved fodder availability is expected to increase livestock gross returns by 10% with an additional expenditure of 5% towards management.

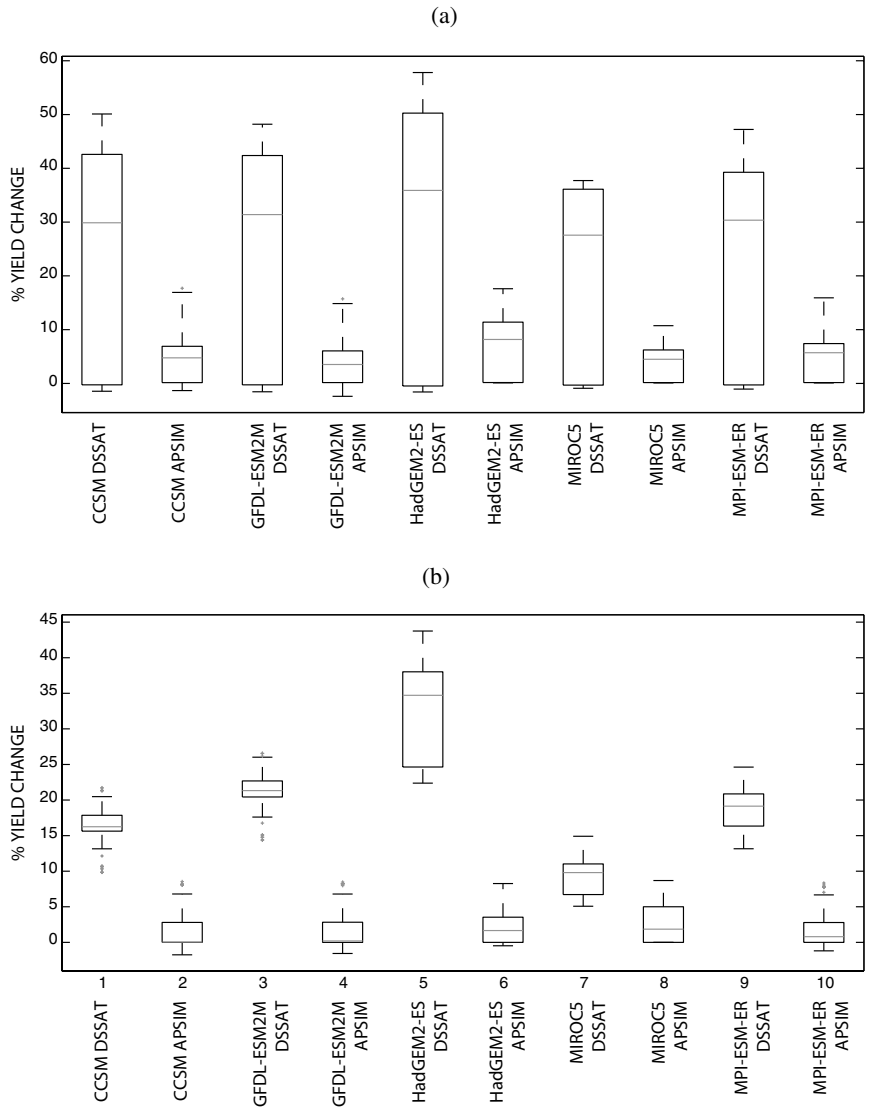


Fig. 10. (a) Percentage yield change under RCP8.5 mid-century climate conditions, with altered DOS, (b) percent yield change under RCP8.5 mid-century climate conditions with altered plant population.

Both APSIM and DSSAT crop simulation models were forced with the future climate projections of five selected GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5 and MPI-ESM-MR) and the results are presented in Fig. 10 DSSAT and APSIM simulated maize crop yields under RCP8.5 mid-century conditions with changed DOS to be earlier and irrigation infrastructure showed that the crop yields would significantly increase compared to existing DOS practices in the future.

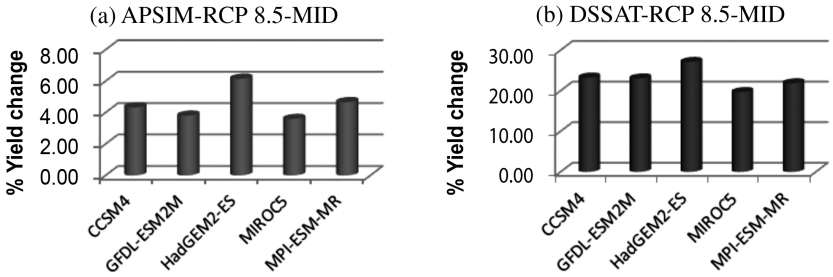


Fig. 11. DSSAT and APSIM projected changes in maize grain yields with DOS adaptation compared to climate-impacted future yields without adaptation in Coimbatore.

Adaptation options such as altering the sowing window and changing the plant population reduced the impact of climate change on maize productivity and increased maize yields relative to baseline conditions. The results indicated that, even in the future climate scenarios, a normal sowing window would increase grain yields. All the climate models projected positive yield deviations, which ranged from 14.82% to 18.37% in DSSAT and 3.38% to 5.55% in APSIM. Increasing plant population to eight plants per square meter also increased yield. The yield deviation ranged from 8.23% to 23.69% in DSSAT and 2.03% to 2.54 % in APSIM (Fig. 11).

Farm income impacts of the adaptation package were simulated using TOA-MD framework. The effects of other components of the adaptation package were estimated based on information from RAPs, and discussion with experts. As outlined earlier, improved water use was expected to contribute for 10% improved returns from other crops by reducing water delivery losses to maize crops through improved water delivery with an amortized irrigation infrastructure investment of Rs. 25,000 per hectare of maize crop. This was also expected to contribute for improved fodder sorghum yield, which would improve livestock income by 10% with 5% additional variable cost. These returns and costs along with returns and costs from maize crop with DOS adaptation were used in the TOA-MD model to assess the overall impact of the adaptation package on the farm households in terms of net returns, *per capita* income, and poverty levels.

Integrated Assessment Results

In considering the impact of climate change and the adaptation package on the maize-based production system in the TOA-MD framework, we compare sets of two systems characterized by technology/climate combinations, current and future with trends, and with and without adaptations. Results of the integrated assessment for these systems are presented in this section by answering three core questions.

AgMIP protocols were used for computing climate-impacted yields, costs, and returns for maize crop (Rosenzweig *et al.*, 2013). For other activities, values were

projected depending on the three questions outlined above (climate sensitivity, climate impact, and adaptation impact) and the system addressed based on RAP information. In our integrated analysis results presented in the following sections, references to APSIM-, DSSAT-, and GCM-related farm returns, *per capita* income, and poverty rates are to be understood as relating to the whole farm TOA-MD results that used projections from the crop model/GCM combinations as TOA-MD inputs.

To test the impact of the adaptation package, maize yields under the DOS adaptation component, a "relative yield" parameter was estimated by dividing the simulated future yields with DOS by the simulated future yields without DOS (but with climate change). These yield estimates were used to derive relevant per farm revenue, cost and return variables for maize.

Core Question 1: What Is the Sensitivity of Current Agricultural Production Systems to Climate Change?

This addresses the issue of how the present production system would respond if the future climate scenario unfolds as it is at present (see Table 5 and Fig. 12). Currently existing (System 1) returns are characterized by actual farm returns based on survey data. Returns for the current system under climate change (System 2) were calculated using the relative maize yields (ratio of climate-impacted yield projections to baseline values), as described by AgMIP protocols (Rosenzweig *et al.*, 2013). Variable costs were also estimated for System 2 as per AgMIP protocols. For crops to which no crop models were applied, climate-impacted farm incomes were computed with respect to literature suggestions (e.g., Kriegler *et al*., 2012). Different impacts of yields and prices are perceived for vegetable, pulse, groundnut, and sorghum crops when they are subjected to climate changes. A 10% negative gross income impacts for the farms with proportional changes in costs and net returns per farm. Livestock incomes of farms were also subjected to 5% negative income impacts per farm with proportional cost and net income changes. Literature (e.g., Rowlinson, 2008; Singh *et al*., 2012) suggests that milk yields, feed uptake, and conversion efficiencies would be negatively impacted by climate change.

Simulated relative maize yields (which are the ratios between simulated and current yields) were less than one with APSIM-based estimates under an irrigated maize system across all GCMs, which indicates declines in yield. DSSAT projections presented mixed results with GFDL-ESM2M and HadGEM2-ES projecting negative yield impacts of 3.99% and 8.57%, respectively, and the other GCMs projecting varying positive impacts. MIROC5-based DSSAT projected a high 31% positive impact. Generally, across all GCMs APSIM projected higher negative yield impacts than DSSAT. When these maize yield impacts were analyzed together with other farm activities, in TOA-MD for whole farms, the "losers" (i.e. those whose farm income are negatively affected by CC) were in the range 87.67% to 91.75% except

Table 5. Sensitivity of current irrigated maize production system in Tamil Nadu to climate change.

Models/Economic Results	CCSM4		GFDL-ESM2M		HadGEM2-ES		MIROC5		MPI-ESM-MR	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
Observed mean yield (maize kg/ha)	7039	7039	7039	7039	7039	7039	7039	7039	7039	7039
Mean yield change (maize) (%)	−14.16	3.72	−15.60	−3.99	−20.25	−8.57	−8.02	31.00	−15.17	12.90
Losers (%)	87.67	71.41	88.71	78.99	91.75	82.99	82.98	44.90	88.43	62.02
Gains (% mean net returns)/farm	6.04	8.53	5.88	7.38	5.37	6.80	6.72	13.71	5.92	10.08
Losses (% mean net returns)/farm	−16.99	−14.24	−17.28	−15.27	−18.30	−16.01	−15.81	−12.20	−17.20	−13.31
Net returns without climate change (INR)/farm	110966	110966	110966	110966	110966	110966	110966	110966	110966	110966
Net returns with climate change (INR)/farm	95288	102394	94713	99317	92852	97524	97691	113272	94877	106060
Per capita income without climate change (INR)/farm	34791	34791	34791	34791	34791	34791	34791	34794	34791	34792
Per capita income with climate change (INR)/farm	30997	32717	30858	31972	30407	31538	31578	35350	30897	33604
Poverty rate without climate change (%)	34.45	34.45	34.45	34.45	34.45	34.45	34.45	34.45	34.45	34.45
Poverty rate with climate change (%)	46.20	41.42	46.61	43.42	47.96	44.64	44.51	35.11	46.49	39.16

60 INR = 1 US$, poverty line = 1.25 US$/person/day.

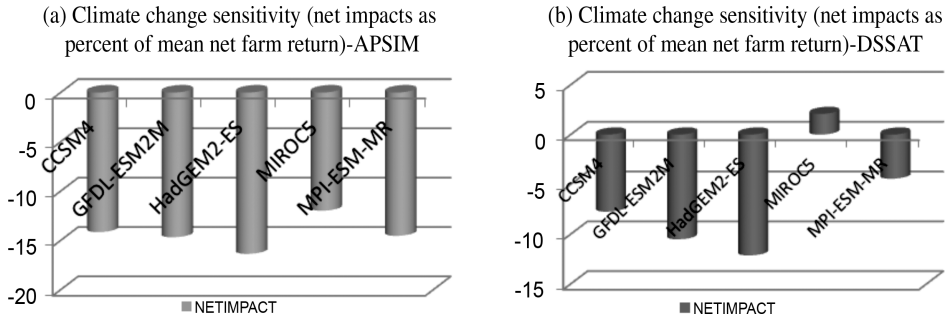


Fig. 12. Sensitivity of the current irrigated maize production system in Tamil Nadu to climate change.

for MIROC5 where it was 82.98% in the APSIM simulations. Losers were less in MIROC5, at 44.9% in the DSSAT simulation. Gains to the production system in APSIM ranged from 5.37% to 6.72% and 6.80% to 13.71% for DSSAT. APSIM projected overall negative impacts that ranged from 9.09% to 12.94%, whereas DSSAT projected similar but lower negative net impacts that ranged from 3.23% to 9.21% across different GCMs, except for MIROC5, with which DSSAT projected a positive impact of 1.51%. Simulated net farm returns, *per capita* incomes, declined across all five GCMs for APSIM and DSSAT farms except in MIROC5 for DSSAT, in-line with crop yield simulations. Poverty rates across farms thereby increased across all GCMs for APSIM and DSSAT.

In general, all APSIM simulations relating to Core Question 1 consistently indicated lower yields under climate change, lower mean net returns, lower *per capita* income, and higher poverty levels for System 2 on irrigated maize-based farms. DSSAT results projected positive impacts. The results were fairly consistent across GCMs between APSIM and DSSAT. Maize crop yield as such is sensitive to the crop model used to predict yields, followed by climate projections represented by the GCMs. At the farm level, other system activities influence the sensitivity of the whole system to climate change.

Core Question 2: What Is the Impact of Climate Change on Future Agricultural Production Systems?

This question addresses the issue of how the present production system would evolve into the future without climate change and how that future system would respond to climate change as projected by different GCMs (see Table 6 and Fig. 13). It is a difficult proposition to project future production systems, and we have approached this as a two-part exercise. Maize yields, which were simulated using crop models for the future system without climate change, were projected by using trends from global economic model projections. Other components of the system including other

Table 6. Impact of climate change on future irrigated maize production system in Tamil Nadu.

Models/Economic Results	CCSM4		GFDL-ESM2M		HadGEM2-ES		MIROC5		MPI-ESM-MR	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
Projected mean yield (maize kg/ha)	13867	13867	13867	13867	13867	13867	13867	13867	13867	13867
Mean yield change (maize) (%)	−14.16	3.72	−15.60	−3.99	−20.25	−8.57	−8.02	31.00	−15.17	12.90
Losers (%)	93.52	57.22	94.70	77.50	97.25	86.44	85.80	11.41	94.38	34.12
Gains (% mean net returns)/farm	4.14	7.49	4.02	5.57	3.73	4.80	4.84	20.46	4.05	10.88
Losses (% mean net returns)/farm	−15.67	−8.84	−16.49	−11.02	−19.33	−12.84	−12.61	−7.00	−16.26	−7.50
Net returns without climate change (INR)/farm	238647	238647	238647	238647	238647	238647	238647	238647	238647	238647
Net returns with climate change (INR)/farm	204311	234221	201880	221260	194049	213710	214468	279980	202580	249643
Per capita income without climate change (INR)/farm	91685	91685	91685	91685	91685	91685	91685	91708	91685	91685
Per capita income with climate change (INR)/farm	80621	90259	79837	86082	77314	83649	83894	105003	80063	95228
Poverty rate without climate change (%)	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.73	2.74	2.74
Poverty rate with climate change (%)	4.19	3.41	4.28	3.73	4.58	3.98	3.76	2.69	4.24	3.11

60 INR = 1 US$, poverty line = 1.25 US$/person/day.

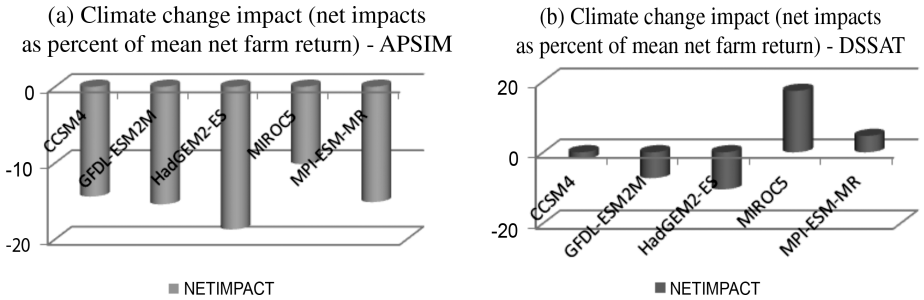


Fig. 13. Impact of climate change on future irrigated maize production system in Tamil Nadu.

crops and livestock incomes, costs, and returns were projected by using information derived from the RAPs and relevant literature.

To compute future system maize yields, present farm yields were adjusted by multiplying with autonomous yield growth trends obtained from global IMPACT model projections using the reference scenario with no climate change for maize yields in the Cauveri basin of India, which projects yields for the period from 2005–2050. As per IMPACT model projections, a factor of 1.97 was used to multiply the present yields to the future without climate change. Similarly an adjustment factor of 1.4 was used to scale producer prices for the maize produce in computing the returns. The variable cost of maize cultivation was also scaled up by 1.97.

Besides maize yields per hectare, incomes and costs of non-modeled activities of the system were modified as derived from the RAPs. Future farm size is expected to increase by 25%, family sizes are expected to become smaller by 25%, non-farm income is expected to rise by 40%, and incomes and costs from other crop activities are expected to rise in line with improving technology and together contribute for an increase of 20% gross income. Variable costs of other crops are expected to contribute an increase of 25% to overall other crops costs. Similarly livestock contribution to system income is expected to rise by 10% due to changes in composition and incomes and costs are expected to rise proportionally.

Changes in maize yields and other variables are likely to occur in this projected future farm system if future climate conditions are imposed on it (System 2 of Core Question 2). Likely changes in maize yields, and costs are estimated based on AgMIP protocols i.e., by using relative yields to calculate climate-impacted yields and proportionate changes in costs (AgMIP Handbook, Appendix 2). Climate-impacted future prices (trends with climate change) of maize were expected to be higher than future prices (trends without climate change) by 15% as projected by the IMPACT model. Based on the RAPs, the incomes for other crops are expected to be reduced by 10%, while costs are expected to be higher by 20% than in the

future system without climate change. Livestock income is expected to decline by 5% with proportionate changes in costs.

Relative yields of maize in the future system with climate change are the same as that in Core Question 1. APSIM projected negative impacts on crop yields for all GCMs in the range of around 14.16% to 20.25%, except for MIROC5 where the impact was less at –8.02% due to higher climate-impacted yield projections under this GCM. In the farm-system-based analysis which includes all activities there were more losers (around 94%) than gainers due to climate change (except in MIROC5-based simulations where the losers were less at 85.80%). Mean net return gains were in the range of 3.73% to 4.14% across all GCMs except MIROC5, where the gain was 4.84%. Losses in net returns were higher, in the range of 12.61% to 19.33 %, which indicates that net impact is of similar magnitude; this has contributed to reductions in observed *per capita* incomes for productions systems with climate change and also increased poverty rates.

DSSAT projected mixed yield results. Positive net impacts were observed in mean farm net returns relating to the GCMs MIROC5 and MPI-ESM-MR of 13.46% and 3.38%, respectively. Hence, reduced household poverty rates were shown when trends with climate change were compared with trends without climate change (Core Question 2, System 2 compared to Core Question 2, System 1). Results from CCSM4, GFDL-ESM2M, and HadGEM-2-ES indicated negative net impacts of 1.35%, 5.45%, and 8.04%, respectively with corresponding influences on poverty rates and net returns. In general, the maize production system seems to be susceptible to climate change impacts even with autonomous productivity trends as projected by the IMPACT model without climate change. MIROC5 and HadGEM-2-ES GCMs seem to have greater influence on the results than other GCMs. In general, climate change impact notwithstanding, future system returns are projected to be higher mainly due to improvements in yields, incomes, prices and, non-farm incomes of the system components. As such, the future system is projected to have almost double the farm net returns, with higher *per capita* incomes and poverty rates drastically reduced to less than 5%. Though future poverty rates were lower, in all simulations using inputs from different GCMs and crop models, poverty increased marginally in the range of 0.37% to 1.84% due to climate change, except in MIROC5 where there was a negligible decline of 0.05%. Climate change impacts seem to be influenced by crop models and GCMs in that order.

Core Question 3: What are the Benefits of Climate Change Adaptations?

By considering the maize yield component of the adaptation package alone, simulated through crop models, relative yields obtained were more than one which implies positive impacts of DOS adaptations on future farm yields and income

Table 7. Impact of DOS adaptation on irrigated maize system in Tamil Nadu.

Models/Economic Results	CCSM4		GFDL-ESM2M		HadGEM2-ES		MIROC5		MPI-ESM-MR	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
Projected mean yield without adaptation (Maize kg/ha)	11904	14346	11705	13282	11062	12660	12754	18122	11766	15612
Mean yield change (maize)(%)/ha	4.33	23.23	3.80	23.02	6.15	27.09	3.59	19.64	4.66	21.82
Adoption rate (%)	92.14	88.86	92.98	93.83	96.11	95.94	84.09	31.02	93.19	74.81
Projected net returns without adaptation (INR)/farm	204318	234233	201891	221440	194269	215511	214469	279980	202593	249643
Projected net returns with adaptation (INR)/farm	241116	272678	240112	271660	243775	278153	241114	285860	241543	273185
Projected *per capita* income without adaptation (INR)/farm	80623	90262	79841	86140	77385	84230	83894	105003	80067	95228
Projected *per capita* income with adaptation (INR)/farm	92480	102651	92157	102323	93337	104415	92480	106898	92618	102814
Projected poverty rate without adaptation (%)	4.19	3.41	4.28	3.73	4.57	3.93	3.76	2.69	4.24	3.11
Projected poverty rate with adaptation (%)	2.93	2.55	2.96	2.69	3.03	2.81	2.84	2.31	2.93	2.48

60 INR = 1 US$, poverty line = 1.25 US$/person/day.

levels from maize crops (see Table 7). When all the components of the adaptation package were considered as a whole in TOA-MD, it proved to be a beneficial option compared to climate-impacted future system with no adaptation package, as indicated by implied adoption rates of about or more than 90% in most GCMs and APSIM and DSSAT, except in MIROC5 simulations where the adoption rates were lowest both for DSSAT with a low 31.02% and APSIM with 84.09%. This is because the yield rate projected for the future system with climate change was the highest in MIROC5. APSIM simulations indicated smaller mean yields increase of 3.59% to 6.15% across the GCMs, while DSSAT projected higher improvements due to adaptation in the range of 19.64% to 27.09%. Poverty rates of households, *per capita* incomes levels, and mean farm net returns have shown similar responses when compared to climate change scenarios as per different GCMs, with and without adaptations.

Net farm returns and *per capita* income increase across all GCMs, and by using both APSIM and DSSAT, though the magnitudes of the increases differed across GCMs. MIROC5 was again associated with least increase, since the projected future yields before adaptation were the highest among the GCMs, and consequently the reductions in poverty were less. Adoption of the adaptation package has helped to increase farm returns, *per capita* income, and reduce poverty, which indicates the mitigating effects and benefits of an adaptation package to climate change. Activities other than maize also appeared to have significant effects in system returns as a whole with implications similar to maize in their influence on *per capita* incomes and poverty rates.

Conclusions and Next Steps

Comparing the current production system (as we have in Core Question 1) and future production systems (as in Core Question 2, i.e., a system with trends and no climate change), there were consistent increases in net returns and *per capita* income and reductions in poverty rates across all GCMs, and also between APSIM and DSSAT results, mainly due to projected autonomous trends in productivity and real prices over time in the business-as-usual SSP2 scenario. Both current and future systems simulations indicate that climate change, by and large, would have negative impacts. Adoption of the adaptation package is seen to produce improvements in net and *per capita* incomes and reductions in poverty. Thus, while irrigated maize production system is both sensitive and susceptible to climate change impacts, both natural trends in productivity improvements and the proposed adaptation package offer scope to reduce climate change impacts on the system.

The irrigated maize production system in Coimbatore, Tamil Nadu was considered for integrated analysis of climate change impacts on farm household

income and poverty through maize yields. Calibrated APSIM and DSSAT crop models were used to simulate maize yields by combining future climate parameters derived from RCP8.5 for the mid-century time frame under the CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR GCMs, and management inputs were derived from economic farm surveys for the period 2008. These yields were converted into projected future farm yields that correspond to the simulations by using the random yield effect model. Global IMPACT economic model projections were used to adjust simulated future maize yields and prices to answer the key questions sought to be addressed through this research. Changes to the future system were projected based on variable values derived from the developed RAPs.

Global impact projections of maize yields for India vary across regions. For our study we have considered projections for Cauvery region of India as the basis for our maize yield projections. For the Cauvery region, the IMPACT model projects yield increases from 4.16 in 2009 to 8.21 tons/ha in 2050, with a growth ratio of 1.97. However, actual yield levels in the study region in the base period are higher, about 7.04 tons/ha. Therefore, using a growth factor of 1.97 to project future yields with trends may overestimate the future yields. Thus there is a need to compare projections from other global models in future work to give more robust projections.

Relating to Core Question 1, APSIM indicated lower yields under climate change, lower mean net returns, lower *per capita* income, and higher poverty levels for System 2, and DSSAT results projected mixed impacts. Maize crop yield is sensitive to the crop model used, followed by climate projections which are represented by the GCMs. At farm level, other system activities influence the sensitivity of the whole system to climate change.

Results of the analysis for Core Question 2 were similar to those from the earlier question in terms of trends. APSIM results in general predicted negative trends and DSSAT gave mixed trends. Future systems in general have higher net farm incomes, higher *per capita* income, and reduced poverty levels due to autonomous technological improvements as predicted by global models and RAPs. Climate change, however, impacts the future system. All GCMs and crop models increased poverty, though marginally, in the range of 0.37% to 1.84%, due to climate change.

By considering potential adaptation options in Core Question 3, an adaptation package with DOS, water saving, and livestock-improving components was considered for the irrigated maize production system of Tamil Nadu. Between APSIM and DSSAT results, there were consistent increases in net returns and *per capita* income and reductions in poverty rates across all GCMs. Thus, while the irrigated maize production system is both sensitive and susceptible to climate change impacts, both natural trends in productivity improvements and adaptations offer scope to reduce climate change impacts on the system. There is thus potential for a majority of the farms (upwards of 90%) to adopt this adaptation package to partially mitigate the negative

effects of climate change. Farms are likely to suffer due to climate change with the current or future production systems, at least marginally, in spite of future yield trends. With adaptation there are increased net farm incomes, *per capita* incomes, and reduced poverty levels that indicate that households may become better off.

The regional integrated analysis in South India can be extended in future by testing the adaptation package in both the current and future systems; using crop models for "baseline" simulations of the future systems, as the management input levels of the farms are projected to be different in the future system from current levels; and using multiple crop models to simulate yields of other system cropping activities that are as yet unsimulated.

References

Antle, J. M. (2011). Parsimonious Multidimensional Impact Assessment, *Am. J. Agric. Econ.*, **93** 1292–1311

Berkhout, F., Hertin, J., and Jordan, A. (2002). Socio-economic futures in climate change impact assessment: using scenarios as 'learning machines', *Global Environ. Change* **12**(2), 83–95.

Challinor, A. J. and Wheeler T. R. (2008). Crop yield reduction in the tropics under climate change: processes and uncertainties, *Agric. Forest Meteorol.*, **148** 343–356.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Jame Y. W and Cutforth H. W. (1996). Crop growth models for decision support systems, *Can J. Plant Sci*., **76**(1) 9–19. D

Kriegler, E., O'Neill, B. C., Hallegatte, S., Kram, T., Lempert, R. J., Moss, R. H., and Wilbanks, T. (2012). The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways, *Global Environ. Change*, **22**(4), 807–822.

Mall, R. K., Singh, R., Gupta, A., Srinivasan, G., and Rathore L. S. (2006). Impact of Climate Change on Indian Agriculture: A Review, *Clim. Change*, **78** 445–478.

Rosenzweig, C., Jones, J. W., Hatfield, J. L. Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Forest Agric. Meteorol*., **170**, 166–182.

Rowlinson, P. (2008). Adapting Livestock Production Systems to Climate Change — Temperate Zones, Livestock and Global Change Conference Proceeding, May 2008, Tunisia.

Ruane, A. C., Goldberg, R. and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol.*, 200. doi: 10.1016/j.agr.formet.2014.09.016.

Semenov, M. and Doblas-Reyes, F. J. (2007). Utility of dynamical seasonal forecasts in predicting crop yield, *Clim. Res.*, **34**, 71–81.

Singh, K. S., Meena, H. R., Kolekar, D. V., and Singh Y. P. (2012). Climate change impacts on livestock and adaptation strategies to sustain livestock production, *J. Vet. Adv.*, **2**, 407–412.

Srivastava, D. K., Shanmugam K. R., and Bhujanga Rao, C. (2010). *MDGs-based poverty reduction strategy for Tamil Nadu*, Monograph No. 6/2010, Madras School of Economics, Chenna, India

Thornthwaite, C. W. and Mather, J. R. (1955). *The water balance*, Laboratory of Climatology, Monograph No. 8, Centerton, NJ, USA.

Turner, A. G. and Annamalai, H. (2012). Climate change and the South Asian summer monsoon, *Nat. Clim. Change*, **2**, 587–595.

Van Vuuren, D. P., Riahi, K., Moss, R., Edmonds, J., Thomson, A., Nakicenovic, N., Kram, T., Berkhout, F., Swart, R., Janetos, A., Rose, S. K., and Arnell, N. (2012). A proposal for a new scenario framework to support research and assessment in different climate research communities, *Global Environ. Change*, **22**(1), 21–35.

This page intentionally left blank

Chapter 10

Climate Change Impacts on Rice Farming Systems in Northwestern Sri Lanka

Lareef Zubair[1,2], Sarath P. Nissanka[2], W. M. W. Weerakoon[3], Dumindu I. Herath[1], Asha S. Karunaratne[6], A. S. M. Prabodha, M. B. Agalawatte[1,2], Rasnayaka M. Herath[3], S. Zeenas Yahiya[1,2], B. V. R. Punyawardhene[3], Janan Vishwanathan[1]. Punya Delpitiya[3], A. Erandika N. Wijekoon[1], Janaka Gunaratna[5], Sewwandhi S. K., Chandrasekara[1], P. Wickramagamage[2,] K. D. N. Weerasinghe[4], Champa M. Navaratne[4], Ruchika S. Perera[2], Asela I. Gunesekara[2], G. M. Pradeep Kumara[1], Daniel Wallach[7], Roberto O. Valdivia[8], and Sonali McDermid[9]

[1]*Foundation for Environment, Climate and Technology, Digana Village, Rajawella, Sri Lanka*

[2]*University of Peradeniya, Peradeniya, Sri Lanka*

[3]*Department of Agriculture, Peradeniya, Sri Lanka*

[4]*University of Ruhuna, Mapalana, Matara, Sri Lanka*

[5]*Rajarata University, Puliyankulama, Anuradhapura, Sri Lanka*

[6]*Sabaragamuwa University, Belihul Oya, Sri Lanka*

[7]*French National Institute for Agricultural Research (INRA), Toulouse, France*

[8]*Oregon State University, Corvallis, OR, USA*

[9]*New York University, New York, NY, USA*

Introduction

Sri Lanka hosts a population of 21 million people in a relatively small area of 65,610 km^2 (Fig. 1). Relatively high rainfall (1830 mm annually) and an equable temperature regime along with fertile soils have enabled the adequate provision of food and water to its people. Although agricultural production has increased over the last century, the population has been rising, reaching 21 million in 2011 from 14.7 million in 1980 (Department of Census and Statistics, 2012b). While advances

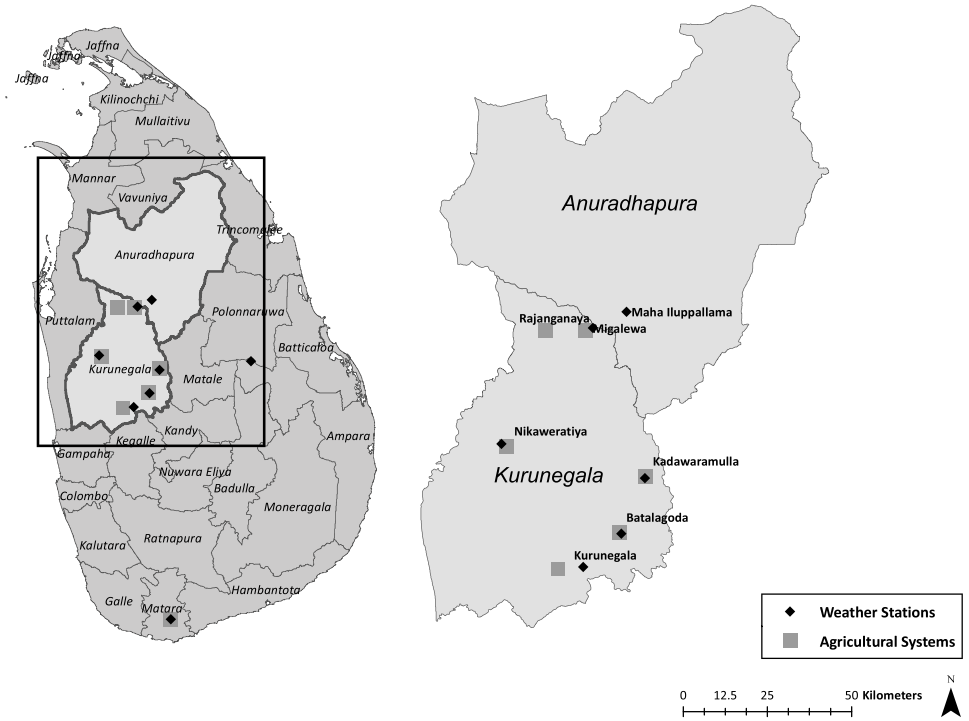


Fig. 1. Sri Lanka and the northwestern study region, with meteorological stations, agricultural research sites, and farming systems.

in agricultural research have been noteworthy, the challenge of securing food supply has been exacerbated by conversion of agricultural lands, internal conflict, limited technological inputs, and periodic shortages of water that constrain yield.

Agriculture accounted for 11.1% of the national gross domestic product (GDP) in 2012, while providing direct employment to 31% of the labor force (Central Bank of Sri Lanka, 2013), indirectly contributing to the livelihoods of up to 70% of the population. Among the crops that account for 78% of the agricultural GDP are rice, tea, and coconut crops which contribute 13.4%, 10.1%, and 10.9% to the agricultural GDP, respectively. Rice is the principal food crop and is grown over approximately 6,135 km^2 in the primary cropping season of Maha (October to March), with cultivation over about half that extent in the secondary seasons of Yala (late April to early September), depending largely on the availability of water. Around 879,000 farmer families are engaged in rice cultivation (20% of the population), providing livelihoods for up to 32% of the population (Department of Census and Statistics of Sri Lanka, 2012a). The country has become nearly self-sufficient in rice production (Department of Agriculture, 2009).

Sri Lanka has achieved tremendous progress since 1950 in crop production and food availability (Department of Agriculture, 2010; Ministry of Agriculture and Agrarian Services, 2008). Yields grew at an impressive rate until leveling off in the mid-eighties (Department of Agriculture, 2009). Sri Lanka's population is anticipated to continue to grow in the coming decades (Department of Census and Statistics, 2012a), creating an ever-greater demand for food security on the household, sub-district, regional, and national scales (Sangakkara and Nissanka, 2008).

The agricultural sector in Sri Lanka is vulnerable to climate shocks (Yahiya *et al.*, 2011; Zubair, 2002). An unusual succession of droughts and floods from 2008 to 2014 has led to both booms and busts in agricultural production, which were reflected in food prices (Gadgil *et al.*, 2011; Zubair, 2005). In both instances, the majority of farmers and consumers were adversely affected. The cultivation of some of the other crops (such as onions, chilies, and vegetables) has become more economically viable especially with the constraint of water. A typical small-scale farming system is represented schematically in Fig. 2. The household unit includes a home garden, other field crops, and livestock.

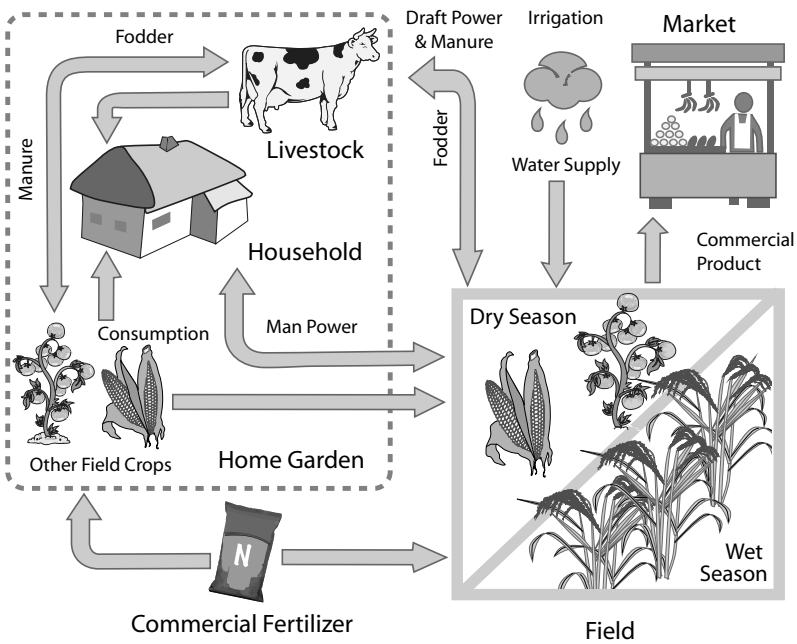


Fig. 2. A schematic of the rice-dominated agricultural system in this region.

At present, the rice-farming systems are under stress due to inadequate returns for the farmers and difficulty in coping with shocks due to climate, pests and diseases, and prices for produce. There are government price-support mechanisms, fertilizer-subsidy schemes, and crop insurance schemes, but the levels of the supports are modest and often do not effectively reach the farmers.

Climate change could compound this situation further if, as projected for South Asia, there is greater tendency for increased temperatures and extreme weather. IPCC (2013) projected that the mean annual temperature shall rise by between 0.5–4°C for the South Asian region for the 2081–2100 period in comparison with 1986–2005, with the lower rise for the lower (RCP2.6) greenhouse-gas-concentration pathways and the higher rise for RCP8.5 (Moss *et al*., 2010). The precipitation is also expected to increase in South Asia (IPCC, 2013) by 0.5 to 4 mm/day on average, with lower values for the RCP2.6 scenario and higher values for the RCP8.5 scenario. While prior assessments have shown consistency across global climate models for temperature projections, there is greater variability among the projections in regard to precipitation (Eriyagama and Smakhtin, 2010; Mahanama and Zubair, 2011). There have been recent modest drying trends in parts of Sri Lanka (Ministry of Environment, 2000, 2010; Zubair *et al*., 2006). Thus it is particularly important to assess climate change projections for precipitation in Sri Lanka, given that annual rainfall has high spatial variability (ranging from 500 mm to 5500 mm); (see, e.g., Lyon *et al.*, 2009). Agricultural water demands have been projected to rise, leaving the northwest Sri Lanka under "Moderate to Severe" scarcity by 2025 depending on water-use practices (Amarasinghe *et al.*, 1999).

Field trials (De Costa *et al.*, 2007; Weerakoon *et al.*, 2005) and crop modeling research (Dharmaratna *et al.*, 2014) suggest that yields in the subhumid regions of Sri Lanka, such as the northwest, are likely to be impacted adversely if temperature increases, although yields could increase if rainfall and CO_2 concentrations rise. The level of sensitivity to temperature is likely to be critical as the rice crop approaches its highest level of temperature tolerance (Weerakoon *et al.*, 2005). Rising sea levels can also affect some of the rice-growing areas if it leads to salination (Ministry of Environment, 2010). There have been a few assessments of the economic impacts of climate change on agriculture in Sri Lanka that link climate projections to yield and estimated economic output (Seo *et al.*, 2005; Kurukulasuriya *et al.*, 2007). These projections relied on statistical relationships between climate and yield projections and pointed to negative economic impacts due to rise in temperature and positive impacts due to rise in rainfall, as found in projections from five GCMs. The work on climate, crop, and economic assessment so far has been limited with regard to model integration, model intercomparisons, and the characterization of uncertainties.

There is a millennium-long history of adaptation (spatially and seasonally) to climate variability across the island through choice of climatically and environmentally appropriate varieties, tailoring of planting season by region, development of appropriate irrigation infrastructure, and social and trade arrangements to suit communal agricultural practices (Zubair, 2005). These adaptation methods afford some potential for coping with future climate change, but they may not be capable of dealing with unprecedented changes. There is an ongoing program of rice varietal improvement at the Department of Agriculture and universities which historically have an excellent track record.

The AgMIP (Rosenzweig *et al.*, 2012) regional assessment in Sri Lanka addresses these issues by generating future climate projections and using them to drive crop models that feed into integrated climate–crop–economic models that in turn quantify climate impacts on livelihoods and poverty. We also test adaptation strategies in this modeling framework under future representative agricultural pathways (RAPs).

Interactions with Stakeholders, Adaptation Options, and Agricultural Pathways

Government policymakers, water-resource managers, local government officials, and farmers have highlighted the need for reliable climate change information, the need to orient research to address the questions they face for allocating resources, and the need for researchers to stay engaged and to disseminate learning.

Interactions with stakeholders

Personnel from the Department of Agriculture involved with the AgMIP regional integrated assessment have solicited advice at departmental meetings and are in a position to contribute to departmental policy.

We have reviewed climate risk information needs with personnel of the Mahaweli Authority of Sri Lanka (MASL), which is a large river basin management agency that provides services for the farmers in its domain (including water distribution, seed distribution, agricultural extension, community development, and enterprise development). The MASL coordinates national water management, to which effort the project investigators have provided a weekly climate advisory.

The University of Ruhuna researchers are engaged in a project to undertake multi-sectoral, multi-institutional, community-based climate risk management in the Nilwala river basin in the south (Zubair *et al.*, 2014). The perspectives of farmers and officials in this region regarding climate change and adaptation were solicited.

We also interacted with bulk purchasers of rice husks for energy conversion and rice for export as regards their needs for climate based predictions and projections of rice harvests (Zubair *et al*., 2014).

Key decisions for national policymaking

Among the key decisions for rice farming systems for the decades ahead are development of national plans for agriculture, land and water resources, food security, environment, poverty alleviation, and guidance for long-term infrastructural investments.

Potential adaptation strategies

Based on a review of national policy documents related to agriculture and climate change adaptation (e.g., Ministry of Agricultural Development and Agrarian Services, 2007; Ministry of Environment, 2010), assessments of researchers, and interactions with stakeholders including farmers, the following adaptation strategies have been proposed: (1) investment in research, innovation, and technology diffusion; (2) promotion of better-adapted cultivation practices and adaptive management of farming systems; (3) risk management of shocks to the farm economy due to climate, pest, diseases, and market volatility; (4) decrease in food losses from farm gate to consumption; and (5) restructuring of policies on farming subsidies, price supports, crop insurance, and trading policies. These policy interventions can be sharpened and prioritized with better information on climate change and its impacts.

Farmer perceptions of climate change and potential adaption

Researchers solicited farmer perspectives in the Kurunegala (Migalewa, Kadawaramulla), Ampara (Mahawanawella), and Matara districts (Nilwala Basin) (Fig. 1) — details in Zubair *et al*. (2014). Farmers in Migalewa perceive the following as major climate-related problems:

- Climate: (1) Changes in total seasonal rainfall; (2) changes in starting date and duration (number of days) of growing season; (3) increase in occurrence of drought; (4) more frequent drought following intense rainfall.
- Crops: Increase in occurrence of crop damages and reduction in harvest due to drought.
- Water supply: (1) drop of groundwater level; (2) decrease of water supply for cultivation; (3) reduction in the duration of water supply for cultivation.
- Pest and diseases: (1) appearance of new diseases and pest attacks.

While issues related to flooding and deforestation were not discounted, these were not a priority for the farmers. They identified the following as practical adaptation options: (1) application of organic fertilizers, insecticides, and herbicides; (2) use of drought-tolerant varieties and shorter-duration crops; (3) change of seasons for cultivation and of planting dates; (4) crop diversification and intercropping; (5) rainwater harvesting; and (6) diversification of livelihoods and non-agricultural income sources. Farmers did not think it was practical either to undertake drip irrigation or energy-intensive cultivation.

Constructing Representative Agricultural Pathways

Representative agricultural pathways (RAPs) ensemble an overall narrative description of a plausible future development pathway and key variables with qualitative storylines and quantitative trends — consistent with higher level pathways such as SSPs and RAPs developed by the AgMIP global modeling group (Rosenzweig, *et al*., 2013a) described further in Part 1, Chapter 5 in this volume.

RAPs were constructed in consultation with researchers and officials, officers of the Department of Agriculture, and the other departments based on literature from several government agencies, consultation meetings, and iterative review. The salient projected changes that are most likely in the coming decades are:

- The current trend of economic growth is projected to continue.
- Population growth rate remains low and urban population increases while rural household size decreases, and farm size declines.
- Rice productivity shall be adversely affected due to deterioration of soil fertility, extreme weather events, climate change, and phasing out of fertilizer subsidies (without adaptation).
- Transportation infrastructure improves and trade policy encourages exports and imposes high taxes on imports of food that can be grown locally.
- Technology developments in the rice sector with high-yielding, drought- and flood-tolerant cultivars, and improved crop management practices shall improve rice productivity.

Summary Narrative of the Adopted RAP

Best practices are implemented in a context of economic growth, low population growth, urbanization, and increasing productivity in the rice sector in a business-as-usual scenario. The government invests more in agriculture to improve food security through self-sufficiency in rice within a framework that promotes the ability of the rice sector to cope with impacts of a variable climate. This is done in a

context of deteriorating biophysical conditions and shortage of labor with decreasing household and farm sizes. Research and development on high-yielding, drought- and flood-tolerant varieties are introduced with enhanced crop management practices to mitigate climate change impacts on rice productivity. The use of organic fertilizers will be promoted while reducing the application of inorganic fertilizers, by phasing out past subsidy schemes. The irrigation/water management system continues to be adapted so as to cope with drought conditions, even while water available for agriculture is reduced.

An associated DevRAP matrix (Table 1) was developed based on the AgMIP methodology (see Part 1, Chapter 5 in this volume) detailing the biophysical, institutional/policy, socio-economic, and technological parameters that characterize the future biophysical and socio-economic conditions, including the likely direction and

Table 1. The variables or indicators which were quantified in the DevRAP matrix were classified under biophysical, institutional and policy, technological, and socio-economic categories. The magnitude of the anticipated change with increasing time is represented by the slope of the arrow.

Category	Variable/Indicator	Direction and magnitude of change
BioPhysical	Rice land degradation	↗
	Water availability	↘
	Land use	↘
Insitutional/Policy	Input subsidies (fertilizer)	↘
	Infrastructure/rural/agricultural access roads/irrigation	→
	Trade policy/taxes on import and export	↗
	Investment on R and D	→
Socio-Economic	Labor availability	↘
	Off farm employment	↗
	Cost of Production	↗
	Farm Size	→
	HH size	→
Technology	Improved rice cultivar productivity trends	↗
	Improved management practices	↗
	Mechanization for cultivation	→

Unchanged	Low increase	Low-Medium Increase	High Increase	Low Decrease	Low-Medium Decrease	High Decrease
→	→	↗	↗	→	↘	↘

magnitude of change and the confidence of all the variables were assessed with the involvement of experts.

In relation to the biophysical parameters, temperature changes and land degradation were identified as important, while there was low confidence on the precipitation increases that have been projected in the past. Among the socio-economic parameters, the current and likely future dearth of agricultural labor and outward migration for employment were identified as important parameters. Among the institutional and policy changes, a reduction in fertilizer subsidies is anticipated, even while investment in the agriculture sector could increase and the coordination among different agencies dealing with agriculture could improve. In the technological realm, it is anticipated with high confidence that farmers will have improved access to information on markets, weather, and climate in the future and that improved varieties of rice will become available.

Data

Sri Lanka has rich archives of agronomic data (Pain, 1986; Wickremasinghe, 2006), which have led to (1) long-term studies on crops, including detailed field trials and coordinated rice trials; (2) long-term climate data at fine resolution (e.g., Zubair, 2004); (3) household-level survey data and aggregated data for economic analysis and (4) data from rice research stations and university research programs.

Climate data

Station data

Meteorological data for Batalagoda (7.51° N, 80°43' E), Maha Illuppallama (8°10' N, 80°45' E), and Maho (7°82' N, 80°27' E) of precipitation, maximum temperature, and minimum temperature were obtained for the period of 1980–2012. Daily rainfall, minimum and maximum temperature, atmospheric pressure, and sunshine hours are recorded at these stations (Zubair *et al*., 2014).

Reanalyses data

The AgMERRA data produced by the AgMIP Climate Team (Ruane *et al.*, 2014) from the MERRA data (Rienecker *et al.*, 2011) were used for gap-filling and for variables that were not available, after applying necessary bias-corrections.

Climate change model simulations and scenarios

The data from the 20 GCMs in the CMIP5 archive (Taylor *et al.*, 2012) were used for projecting future climate. Analysis was restricted to five GCMs (CCSM4,

GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR) that were identified by AgMIP as relatively skillful in reproducing the climate over South Asia by AgMIP.

Crop Data

Aggregate historical data on area of cultivation, production, and yield are estimated collectively by several government agencies.

Rice experimental trials

Experimental data for rice trials are available from the Department of Agriculture (Batalagoda, Maha Illupallama, and other field stations). Calibrations were carried out on the following varieties of data in wide spread use in the region — Bg300 (three months duration), At308 (three months), Bg357 (three-and-a-half months), Bg358 (three-and-a-half months), and Bg379-2 (four to four-and-a-half months). Further details are available in the chapters on calibration in Zubair *et al*. (2014) including for other varieties (Bg250, Bg304, Bg307, Bg94-1).

Data from (1) detailed field trails and (2) Coordinated Rice Variety Trials (CRVTs), were used for calibration and evaluation of models. These detailed experiments, conducted at the Rice Research and Development Institute (RRDI) of Sri Lanka at Bathalagoda, from 2001–2010 in the major (Maha) and minor (Yala) growing seasons with two nitrogen fertilizer levels. CRVTs were conducted at two different agroecological regions of RRDI and FCRDI (Field Crop Research and Development Institute (FCRDI) at Maha Illuppallama), during the two growing seasons from 2000 to 2008.

The size of the experimental plot was 18 m^2 (6 m $\times$ 3 m). Recommended standard procedures by the Department of Agriculture (DOA) were adapted for rice crop management. Irrigation was provided, then the land was ploughed, crop residues of the previous season were incorporated three weeks before planting, and the soil was puddled continuously with subsequent ploughing/harrowing actions undertaken at least twice to make the fields weed-free and level before planting.

The crop was established by broadcasting pre-germinated seeds (direct seeding at a rate of around 350 plants/m^2). Irrigation water was provided as required and maintained at a standing water level of about 25 mm starting from one week after emergence until grain-filling was completed.

Fertilizer application was carried out as recommended by the DOA. Split application was practiced as at planting, first top dressing (two weeks after planting), second top dressing (five weeks after planting), third top dressing (seven weeks after planting) for three-month varieties, and additional application of N at booting stage for three-and-a-half and four month varieties. Medium fertilizer treatment represents

the DOA recommended fertilizer levels. Continuous monitoring of pest and disease outbreaks was undertaken and appropriate control measures were applied whenever necessary.

For the detailed experiments, growth and development parameters (plant height, leaf area, and tiller count) were recorded at regular intervals, along with time taken to panicle initiation, anthesis and maturity stages. Yield and yield components were measured at maturity. For CRVT experiments, time taken to heading and harvesting stages, and yield measurements were recorded.

Data for Integrated Assessment

Researcher-conducted surveys of farming systems are available for a cross-section of farmers in selected locales in the Kurunegala district (Fig. 1). These locales are referred to as Set 1 (Nikaweratiya, Rajangane, and Batalagoda) and Set 2 (Kadawaramulla, Migalewa) and details are provided in Zubair *et al*. (2014). All of the locations except Kadawaramulla practice cultivation in the minor Yala season. In Kadawaramulla there is a system of irrigation in alternate years for Yala for each bank of the feeder irrigation canal. Including Kadawaramulla ensures that we capture practices that are representative of the entire district. Although we have conducted surveys for two successive Yala seasons for Kadawaramulla, the year it received irrigation coincided with a drought that devastated the rice crop during the Yala season. So for Set 2, to be able to represent both seasons, we report here on the results for Migalewa while detailed results for Kadawaramulla are not shown here, but are included in Zubair *et al*. (2014) and in Herath *et al*. (2013).

Soil and climate files were developed for the respective sites based on the recorded information (Mapa *et al.*, 2005). Additional soil testing was undertaken for Kadawaramulla and Migalewa (Zubair *et al*., 2014). Crop management practices for farmer fields were estimated based on the farmer-survey information and standard practices.

Methods of Study

Climate

The work followed methods outlined in the AgMIP Handbook (Rosenzweig *et al*., 2013a) and described further in Part 1, Chapter 3 in this volume.

Quality control

Inconsistent data entries were identified and removed. Neighboring station data were compared in cases of unusual observations. The solar radiation data were taken from

AgMERRA datasets developed by the AgMIP climate team (Ruane *et al.*, 2014) and compared with estimations from sunshine hours based on a previously calibrated algorithm (Samuel, 1991).

Missing values of variables and gaps from data removed for quality control were filled in. If the gap was less than two days, it was filled based on the values on both sides of the gap and after cross-checking with observed values of neighboring stations for validation in the case of temperature. Other gaps of data (more than two days) were filled by using the AgMERRA dataset prepared by the AgMIP climate team with bias-correction.

In instances where the farm locations were not close to the meteorological stations, a method of extrapolation developed by the AgMIP Climate Team based on the high-resolution monthly spatial climatologies developed by WorldClim was used.

Mid-20th century projections

The work reported here focused on GCM-based estimates for the mid-20th century (2040–2070) under a high-emission-concentration pathway (RCP8.5) (Moss *et al.*, 2010; Taylor *et al*., 2012). The results from the following five GCMs were used for some of the more detailed analysis as they represent the South Asian region better: CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR (labeled as E, I, K, O, and R respectively). The methodology for downscaling the climate projections to each station was based on the "delta method" (Wilby *et al*., 2004). The implementation is described in detail in Part 1, Chapter 3 in this volume. Time series at individual stations were created by modifying the meteorological station data with mean monthly spatial differences provided by the WorldClim dataset (Hijmans *et al*., 2005).

The significance of future change in this average temperature precipitation and of all 20 GCMs were tested based on whether there was a change of two standard deviations of yearly variation (see Part 1, Chapter 3 in this volume).

Crop Model Calibration and Simulations

Calibration

Calibration of DSSAT-CERES-Rice version 4.5 (Jones *et al.* 2003), and APSIM-ORYZA version 7.5 (Keating *et al.*, 2003) crop models was undertaken for the commonly used varieties of rice in Sri Lanka for which experimental data were available (Bg 250, Bg 300, Bg 357, Bg 358, Bg 379-2, At 307, and At 308). These data are based at Batalagoda and Maha Illupallama, along with the data from the national CRVT for the same locations.

Table 2. Genetic coefficients generated for DSSAT-CERES rice crop model for four cultivars.

	P1	P2R	P5	P2O	G1	G2	G3	G4
Bg 300	407.9	134.7	396.2	12.6	50.7	0.026	0.95	1.1
Bg 357	382	122.5	393.8	11.5	55.5	0.025	0.95	1.23
Bg 358	435.6	72.5	500.1	10.7	50.3	0.019	0.69	1.1
At 308	400.8	50.3	400.7	12	68.5	0.019	1	1.2
Bg 379-2	662.9	140.9	437.1	10.8	58.9	0.03	0.5	1.16

DSSAT CERES-Rice calibration

Detailed experiments and CRVT from two experimental sites at Batalagoda and Mahailluppallama were used for generalized likelihood uncertainty estimation (GLUE) runs, initially only for phenology. Then GLUE-estimated phenology was fixed for the estimation of growth parameters (G1, G2, G3, G4) by using measured growth variables in detailed experiments. The grain size (G2) was calculated for selected varieties based on historical data and fixed for the variety. Therefore, only G1, G3, and G4 were estimated from GLUE runs of detailed experiments. The crop model simulations were evaluated by using model efficiency criteria for leaf-area index (LAI), tops weight, tiller number, and yield predictions for detailed experiments, and yield only for CRVTs. The genetic coefficients obtained are provided in Table 2.

APSIM calibration

The same dataset used for DSSAT calibration was used for APSIM calibration. The APSIM-ORYZA model parameters of rice according to different growing stages were considered for the calibration of the respective varieties; these include two photoperiod-sensitive stages and two growth parameters. Developmental stages of the crop model are:

1. DVJR; Development stage in juvenile phase
2. DVRI; Development stage in photoperiod-sensitive phase

} Photoperiod-sensitive

3. DVRP; Development rate in panicle development
4. DVRR; Development rate in reproductive phase

} Photoperiod-insensitive parameters

The fixed values of DVS at important growth stages in APSIM are 0 (at sowing), 0.65 (at panicle initiation), 1 (at flowering), and 2 (at maturity).

Developmental rate parameters (DVS) were calculated by using growing degree days (GDD). GDD were calculated by using T_{max}, T_{min}, and base temperature (T_b),

Table 3. Genetic coefficients generated for APSIM-Oryza rice crop model for four cultivars.

Model parameter	Bg 300		Bg 357		Bg 358		Bg 379-2
	Yala	Maha	Yala	Maha	Yala	Maha	Yala
DVRJ	0.001071	0.001071	0.000878	0.000878	0.000869	0.000869	0.001037
DVRI	0.000853	0.001071	0.000737	0.000878	0.000721	0.000869	0.000285
DVRP	0.000646	0.000646	0.000636	0.000636	0.000641	0.000641	0.000643
DVRR	0.001755	0.001755	0.001729	0.001729	0.001871	0.001871	0.001869
MOPP	13	13	13	13	13	13	11.5

i.e., 8°C. GDD for phenological events were calculated based on the ORYZA-2000 model. The parameters estimated for APSIM inputs are given in Table 3.

DSSAT-CERES and APSIM-ORYZA crop model simulations

DSSAT-CERES and APSIM-ORYZA simulations were undertaken based on the farmer surveys identified as Set 1 and Set 2. These simulations were undertaken with consistent genetic coefficients, consistent choices for management but differentiated by the details of the farm surveys and the soil and weather for Set 1 and Set 2.

The "IT tools" developed by AgMIP were used to undertake the large number of simulations required in a batch mode. The weather, soil, fertilizer, water, and crop management data were incorporated into the input files (i.e., field overlay file, survey data file, and seasonal strategy file) that were prepared for the QUADUI AgMIP IT tool (Rosenzweig *et al.*, 2013a). This enabled the generation of DOME and ACMO files for input into the crop simulations and integrated assessments.

Farm-survey data were used in order to match crop management (Hoogenboom *et al.*, 2010), i.e., planting, harvesting, application of inorganic fertilizer, irrigation, and applications of crop residues and organic manure.

Yields for the "current year" (2012/2013 for Set 1), were simulated for individual farm fields. For Set 2, the current year was September 2011 to August 2012 for Kadawaramulla and September 2012 to August 2013 for Migalewa.

Using these simulated results for the "matched data case" (Rosenzweig *et al.*, 2013a) were obtained where the models use weather, soil, and management for each field to simulate production matched with observed yields for each field. Yields for the future periods (2040–2069) were obtained by using the corresponding climate change scenarios derived from global climate models and observed weather data (Rosenzweig *et al.*, 2013a, 2013b).

In simulating the future period, automatic planting was set within an interval of time with conditions for soil water content (i.e., target rainfall accumulation) specified at 20 mm. The harvesting option was set as "when the crop is mature".

In simulating the future period for Migalewa and Kadawaramulla, automatic planting was set for one-day duration for the planting window and for soil water content specified at 150 mm.

Integrated Assessment

We used the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD) economic model, which is a multi-dimensional impact assessment program that utilizes statistics of farm characteristics (means, standard deviations, coefficients of variation) to simulate the impacts of environmental changes on economic conditions (Antle, 2011; Antle and Valdivia, 2006). In this study we use it to assess climate change impacts on socio-economic aspects of farming systems with the intent of providing support for informed policymaking. The model could be used in the future for prospective evaluation of technology adoption and technology impact assessment, payments for ecosystem services and environmental change impact and adaptation.

The TOA-MD analysis was undertaken for a population of heterogenous farms under one stratum with one production activity of growing rice. These methods were followed to answer the following three "core climate impact questions" as posed by AgMIP (Rosenzweig *et al*., 2013a).

1. What is the sensitivity of current agricultural production systems to climate change?
   This seeks to address the impact of climate change on the current production.
2. What is the impact of climate change on future agricultural production systems?
   This seeks to address the impact of climate change on the future production system. Technological and other developments in the agricultural sector may alter the current production system in the future. Hence vulnerability to climate change may be dissimilar to the case of the current production system, which is described in the Question 1 simulations.
3. What are the benefits of climate change adaptations?
   This line of inquiry seeks to assess the advantages of adaptation strategies in abating deleterious climate change impacts on the future rice-production system. While we have undertaken work on adaptation, it shall be reported in the future.

While TOA-MD analysis was initiated for all of the farming systems, in this chapter results are presented only for Migalewa.

In setting up the TOA-MD model there was one key assumption. The farmer surveys in Migalewa were undertaken separately for each of the two seasons in the same small region. The populations of farmers for each season have similar household economics and use similar crop management practices. In fact, nine

Table 4. Farm sizes and household sizes for the two surveys taken during the Yala and Maha seasons conducted at Migalewa.

Season	Sample size	Farm size	CV of farm size	HH size	CV of HH
Maha	31	0.89	22.16	4.16	29.17
Yala	31	0.82	33.95	4.45	28.91

of the 38 farmers overlapped. For the TOA-MD analysis, these two populations were assumed to provide statistics that are representative of the region for each season. Farm size and household size for the farmers are very close (Table 4) and these farmers were all chosen within an "irrigation block" of the regional office for System H of the Mahaweli River Basin Authority. Thus these two sets of farmers should have similar practices, market conditions, technical resources and settlement histories (Raby and Merrey, 1989). Based on this assumption, the results from both seasons were combined to provide annual estimates.

The two seasons were considered as two crop activities in the TOA-MD model setup. Two sets of crop simulations were undertaken to address the core questions with the use of the climate projections from the five different GCMs.

These two crop simulations were for:

1. Current climate with current production system
2. Future climate with current production system

In addressing Question 1, the first and second simulation sets were compared (i.e., sensitivity analysis of climate change), without setting trends for prices/yields. Similarly for Question 2, the same set of simulations were undertaken with RAPs and trends for prices and yields. Trends for prices and yields were incorporated for Question 2 (impact of climate change on the future system). Trends for prices and yields were obtained from the IMPACT global economic model, with values specified for Sri Lanka (Group 1 in Table 5). We also did a sensitivity test with a second set of trend assessments (Group 2) derived largely from the IMPACT model to better understand the sensitivity to the choices in the RAPs.

Results

Climate results

The climate projections for the mid-century (2040–2069) for Batalagoda, based on 20 GCMs under higher greenhouse gas concentrations (RCP8.5) are shown in Fig. 3. There is a consistent rise in temperature in all 20 GCMs for both seasons. The increase in temperature is nearly consistent across all the months. For the Yala

Table 5. Values for trends for variables and indicators used in the TOA-MD that were obtained mostly from Groups 1 and 2.

Vaiable	Group 1-Trend factors mostly from RAPs		Group 2-Trend factors mostly from IMPACT global model	
	Description	Value	Description	Value
Yield trend τ	RAP defined value	1.25	AgMIP Reference scenario under IMPACT Global model	1.498
Price trend $\varphi 1$	AgMIP Reference price under IMPACT model	1.18	AgMIP Reference price trend under IMPACT Global model	1.179
Price trend $\varphi 2$	RAP defined value (assumed to be matched with cost trend)	1.2	SSP2_HGEM_DSSAT_5crop scenario price Trend under Impact Global model	1.462
Household size (HH)	RAP defined value (percentage decrease)	−16%	RAP defined value (percentage decrease)	−16%
Farm area (Ha)	RAP defined value (percentage decrease)	−18%	RAP defined value (percentage decrease)	−18%
Cost trend (Ψ)	RAP defined value	1.2	Cost from IMPACT model (assumed to be same as SSP2_HGEM_DSSAT_5crop scenario price trend)	1.462
Non-agricultural income (Rs)	RAP defined value (percentage increase)	30%	RAP defined value (percentage increase)	30%

season, there is an increase in temperature ranging from 1.5 to 2.8°C and for the Maha season, there is an increase in temperature ranging from 1.1 to 2.4°C. The monthly climatology of rainfall in the future period shows a significant increase from September to November for all GCM scenarios and less change in other months.

A significance test was undertaken with a change of two standard deviations of yearly variation for either parameter taken as significant for the mean alone, and both mean- and variability-based scenarios (see Part 1, Chapter 3 in this volume). The results show that the temperature rise is significant in both scenarios for all GCM outputs for both Yala and Maha.

For Maha, there is an increase in average rainfall of up to 9.5 mm/day in the future period (with one GCM showing a drop of 0.1 mm/day) from a current average of 6 mm/day. This increase in rainfall is significant in both testing scenarios for both Yala and Maha, for 16 of the 20 GCM outputs including four of the five selected GCMs (except for HADGEM2-ES). Note this exceptional GCM was one of the warmest.

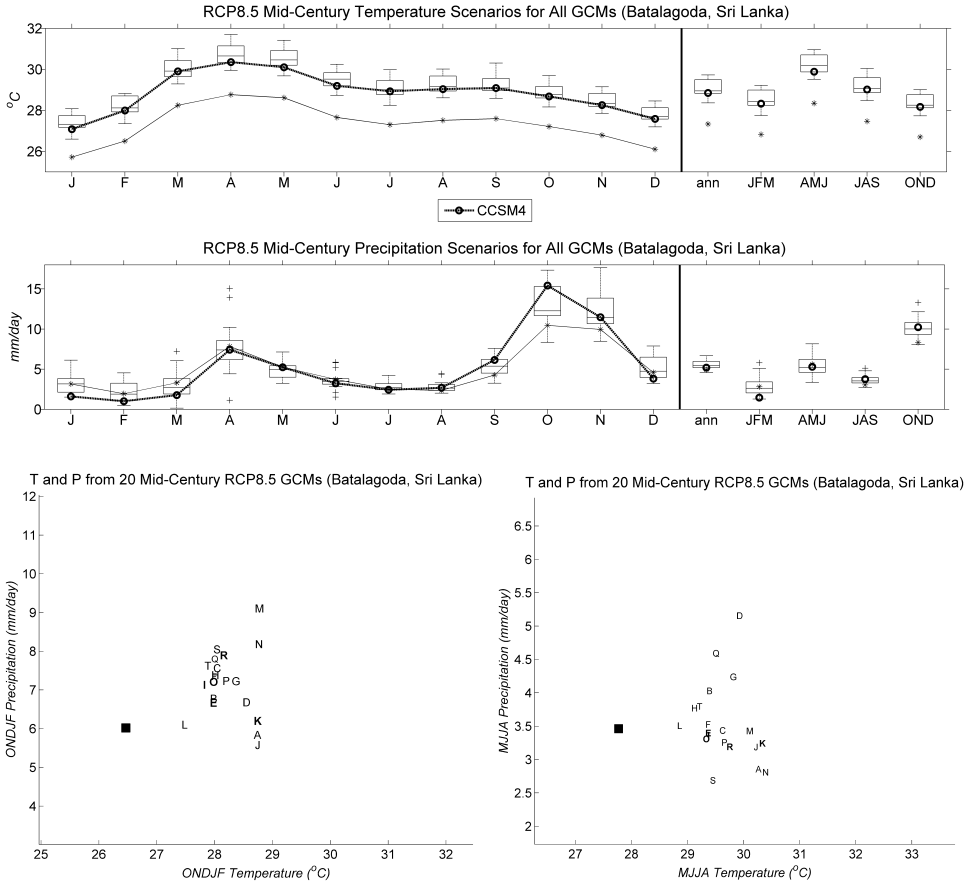


Fig. 3. Top left: The monthly and seasonal climatology for temperature in the present (1980–2010 as a solid line) and in the future projections (2040–2070 as box-and-whisker plots for the 20 GCMs) for Batalagoda in northwest Sri Lanka. The line shows the climatology for one GCM (CCM4) as an example. The letters indicate the respective GCMs and those selected for detailed analysis are shown in red. These are the GCMs CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR and are labeled as E, I, K, O, and R. Top right: Shows the same but at the annual time-step ("ann") and for the seasons of January to March (JFM), April to June (AMJ), July to September (JAS) and October to December (OND). These seasons approximately correspond to early and late Maha (October to March) and Yala (April to September) agricultural seasons. Second panel, left and right: The same as at the top but for precipitation rather than temperature. Third panel: The bottom graphic shows the "seasonally" averaged current (solid square) and future projections (letters as in top panel) and climate projections for the mid-century (2040–2069) under RCP8.5 for Batalagoda. The months in the season most likely to affect the rice crop are chosen — October to February for Maha and April to July for Yala.

For the Yala season, there is an increase in rainfall of up to 2 mm/day for 10 of the GCMs and a decrease in rainfall for the rest of up to 1 mm/day from an average of 3.5 mm/day. However, only 10% of the GCMs showed a significant anomaly (a rise in this instance), and none of the five selected GCMs had a significant change in rainfall.

Crop modeling results

DSSAT-CERES calibration results

Simulated results with DSSAT-CERES for time taken to panicle initiation, anthesis, and maturity from emergence compared well with observed values for detailed and CRVTs experiments. RMSE (root mean square error) was around four to five days for all varieties (see Fig. 4 for calibration results of anthesis and yield for the Bg 300 cultivar). RMSE for yield was lower for the Bg 357 cultivar (425 kg/ha), compared to the other two varieties Bg 300 and Bg 358, which ranged from 1800 to 2000 kg/ha. All varieties had a similar RMSE of ∼1400 for grain yield. Deviations for top weights and grain yields for these varieties compared to those observed were mainly due to biotic stress. For example, CRVTs of Bg 358 recorded lower observed yields due to a pest attack at grain-filling, which could not be controlled in time.

APSIM-ORYZA calibration results

The APSIM-ORYZA model calibration results (Fig. 4) showed a good fit, indicating RMSE for time taken to panicle initiation, anthesis, and maturity, were in the range of three to six days. RMSE for grain yield was around 1000 kg for Bg 300 and Bg 357, while it was higher (1200 kg) for Bg 358. Deviation of simulation for grain yields for these varieties compared to the observed was mainly associated with the biotic stress. For example, CRVTs of Bg 358 recorded lower observed yields due to a pest attack at grain-filling, which could not be controlled in time.

Crop simulation results for farm survey yields and climate scenario effects

Parallel studies were undertaken for two sets of locales chosen from the Kurunegala district as described in the methodology. Set 1 included farm survey data from Batalagoda, Nikaweratiya, and Rajanganaya and Set 2 included Migalewa and Kadawaramulla.

Crop simulations were generated using DSSAT and APSIM crop models. The same genetic coefficients as described above were used. Simulations for the base year (2012–2013), historical period (1980–2010), and five GCMs at mid-century

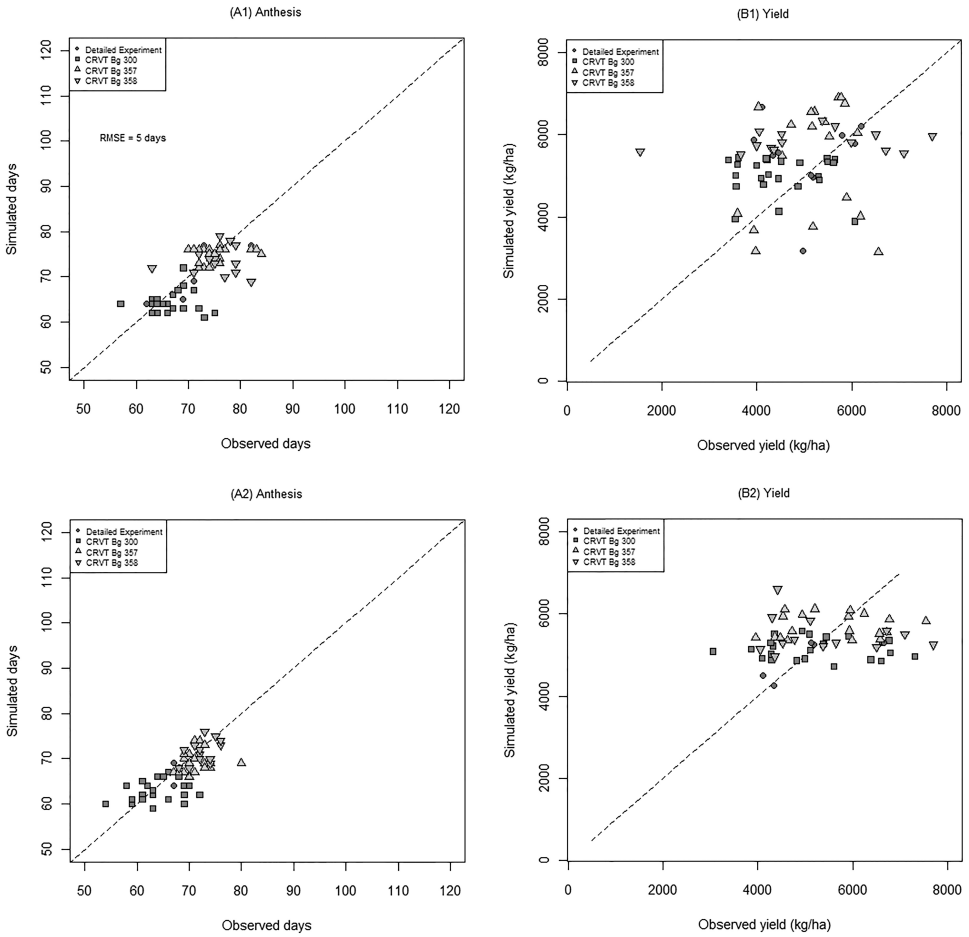


Fig. 4. Comparison between simulated and observed yields with a 1:1 line (- - -) of (A) days to anthesis and (B) grain yield for the rice variety Bg 300 using DSSAT (top row) and APSIM (bottom row).

(2040–2070) for the major and minor seasons were obtained. These results were calibrated and validated accordingly.

SET 1: Batalagoda, Nikaweratiya, and Rajanganaya

Simulation results for the first set (collection of all three locations) for the major and minor seasons of the base year (2012/2013) are presented in Fig. 5. Significant positive relationships were found between observed and simulated rice yields for both seasons for the DSSAT and APSIM crop models. A seasonal comparison revealed slightly greater overestimation for the minor season by DSSAT (RMSE of 1300 kg/ha) than for the major season (RMSE of 1200 kg/ha).

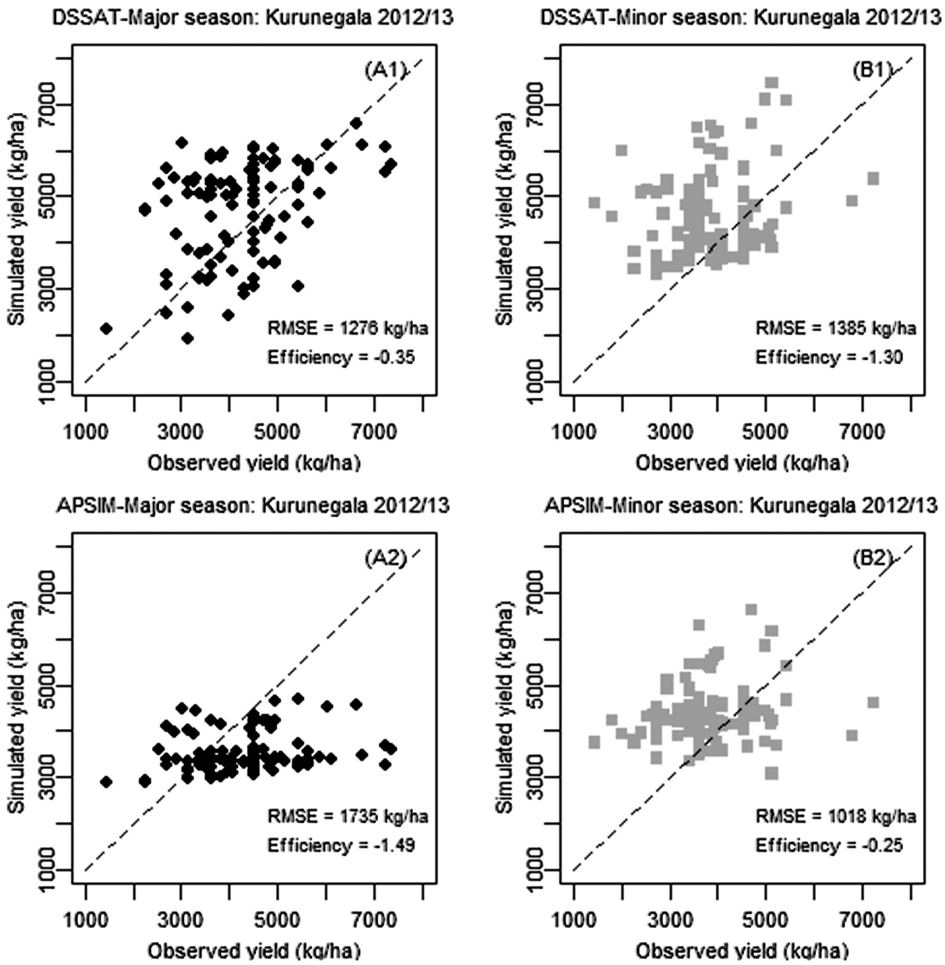
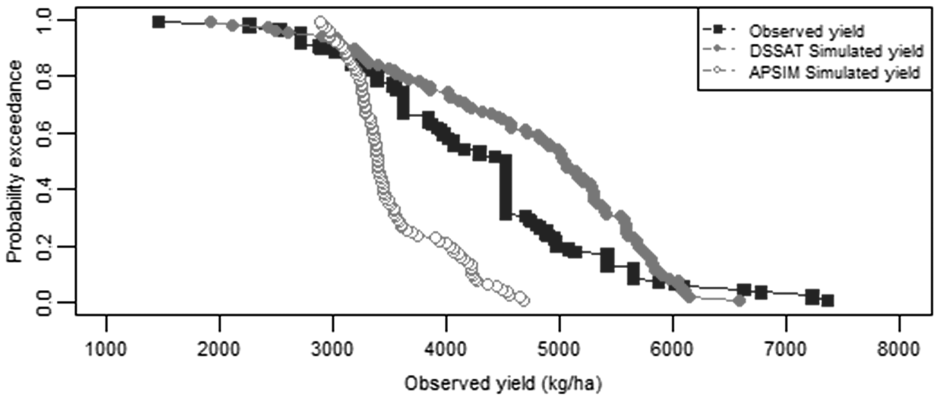


Fig. 5. Comparison between DSSAT-CERES simulated and observed yields of farmer fields in Kurunegala (Set 1) for the base year of (2012–2013) with a 1:1 line (- - -). This is shown for simulations from DSSAT in the top panel for the major (A1) and minor (B1) seasons. The results from APSIM-ORYZA simulations are shown in the bottom panel for the major (A2) and minor (B2) seasons.

However, APSIM simulated higher yields during the major season (RMSE of 1700 kg/ha) compared to the minor season (Fig. 5). Multi-model comparison of the probability of exceedance of simulated vs. observed yield revealed a more-or-less similar relationship between the two crop models for the minor season compared to the major season (Fig. 5).

Our simulations are undertaken with the assumption that the crop is not water-stressed. Water limitation for the rice crop is relatively lower in the major season than in the minor season. Sensitivity of these crop models to water status may have contributed to these differences. Farmer survey revealed that some farmers were

(a) Major season: Kurunegala 2012/13



(b) Minor season: Kurunegala 2012/13

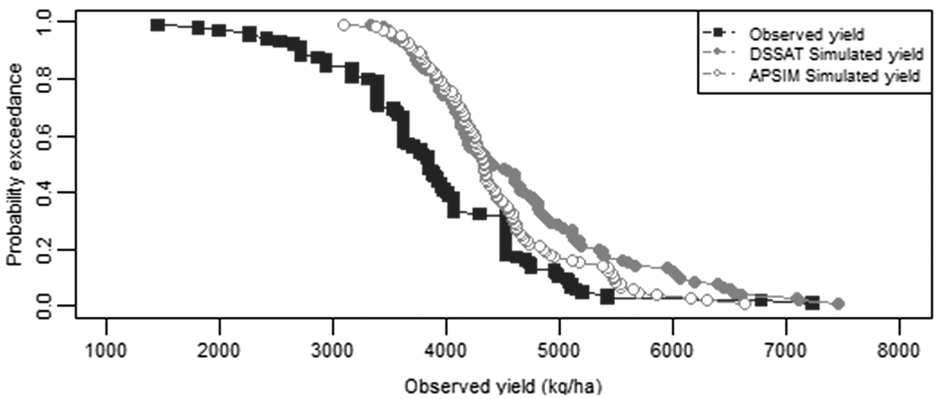


Fig. 6. The probability of exceedance yields for observed and simulated (DSSAT and APSIM) yield for farmer fields in Kurunegala for the base year (2012–2013) for the major (A — top) and the minor (B — bottom) seasons.

unable to get the required fertilizer at the correct time, and the application was delayed particularly in the minor season. Few farmers, especially in the Batalagoda region, also reported that their fields were infested with weeds that they were unable to control. These reasons may have also contributed to lower observed yield for some farmers, though the amount of fertilizer applied remained the same, resulting in higher simulated yields, RMSE, and poorer yield distribution fit for probability of exceedance in both crop models (Fig. 6).

Yield prediction with DSSAT with GCM scenarios

DSSAT results revealed that rice yield is reduced for all GCMs with a different magnitude for each season (Fig. 7). Compared to the baseline period, percentage yield

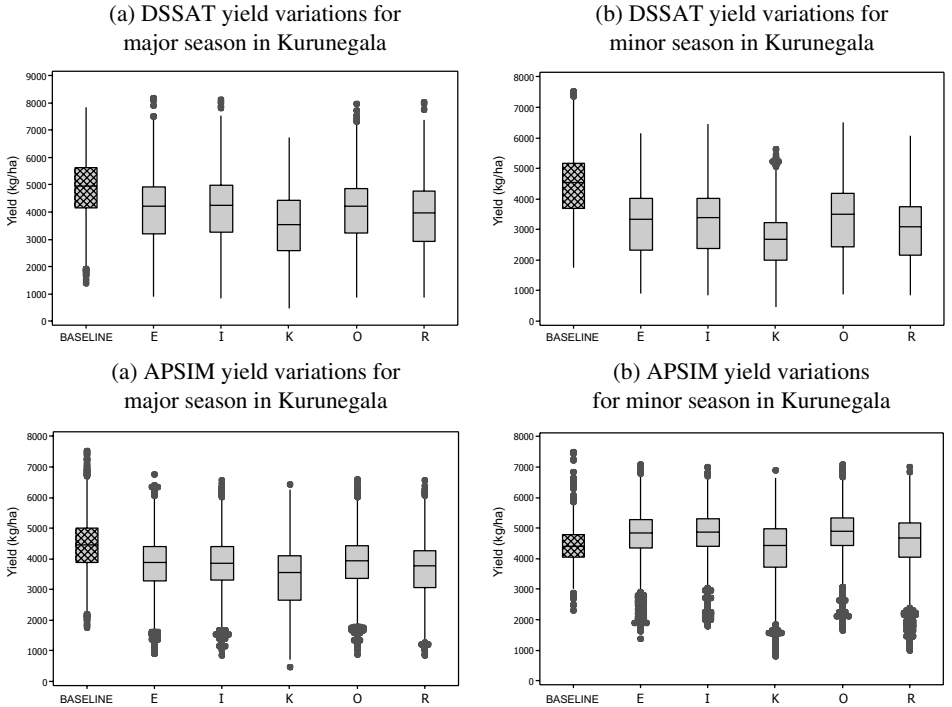


Fig. 7. Top: DSSAT simulated rice yield for the major (A) and minor (B) seasons for five GCMs (mid-century) compared to baseline period for farmer fields. Middle: As in top panel for APSIM simulated rice yield for the major (A) and minor (B) seasons. Bottom: As top for DSSAT simulated rice yield for the major (A) and minor (B).

reductions for the five GCMs CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR (labelled E, I, K, O, and R) were 13, 12, 19, 15, and 16%, while percent reduction for the minor season was 27, 28, 41, 33, and 36%. The highest reduction was observed for the HadGEM2-ES (K) GCM for the minor season being the warmest of selected five GCMs. Since the Yala is the warmer season, it is likely that if temperature rises excessively, then the rice crop which is usually at its higher range of temperature tolerance (Weerakoon *et al*., 2005) shall be adversely affected.

Yield prediction with APSIM with GCM scenarios

Different responses were observed for the climate change yield simulations with APSIM. Though a slight yield reduction was observed for all five GCMs in the major season, higher yields were simulated for four GCMs (except for the HadGEM GCM) in the minor season. Percentage yield reductions observed for the Maha season compared to the base period for the five GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR) were 5, 5, 8, 5, and 6% respectively while only 2% reduction was observed for the HadGEM2-ES GCM for

the Yala season. The other GCMs (E, I, O, and R) simulated 8%, 9%, 9%, and 3% greater yields respectively for the minor season, compared to the baseline period. In both seasons the highest yield reduction was observed for the HadGEM GCM.

SET 2: Kadawaramulla and Migalewa

Farmer-specific rice yields were simulated for Set 2 for the historical period and the projections of the five GCMs of mid-century (2050s) for the major and minor seasons using DSSAT and APSIM.

In the case of Kadawaramulla of Set 2, the rice cultivation was only available for the major season due to a devastating drought in the minor Yala season for which the field survey results are available. We were not able to obtain data for the minor season in years before or after as there is a system of irrigation being provided only on alternate years for this region. The results for Kadawarmulla are included in Zubair *et al*. (2014).

Results of the DSSAT simulations for the historical period of the major and minor seasons for the Migalewa location of Set 2 (Figs. 8 and 9) are qualitatively similar to that presented for Set 1. The RMSE of simulated yields is mostly the same (Fig. 8). The yield distribution as probability of exceedance matches well to the observed farm yield distribution (Fig. 9).

The yields simulated with DSSAT are reduced for all five GCMs for both major and minor seasons (Fig. 10). For Migalewa, the percentage yield losses in the major season compared to baseline for the five GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR) were 6.8, 6.1, 14.5, 7.5, and 7.9% respectively. Similarly for the minor season, the yield reduction was 24.8, 26.7, 36.8, 24.6, and 30.6% respectively. For Kadawaramulla yield reductions in the major

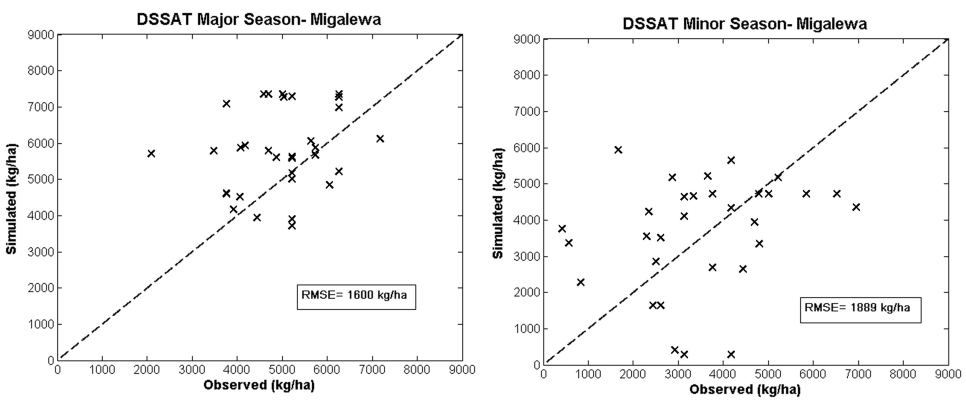


Fig. 8. Comparison between observed and DSSAT simulated yields for farmer fields in Migalewa (Set 1) for (left) major and (right) minor seasons for the base year (2012–2013) with a 1:1 line (- - -).

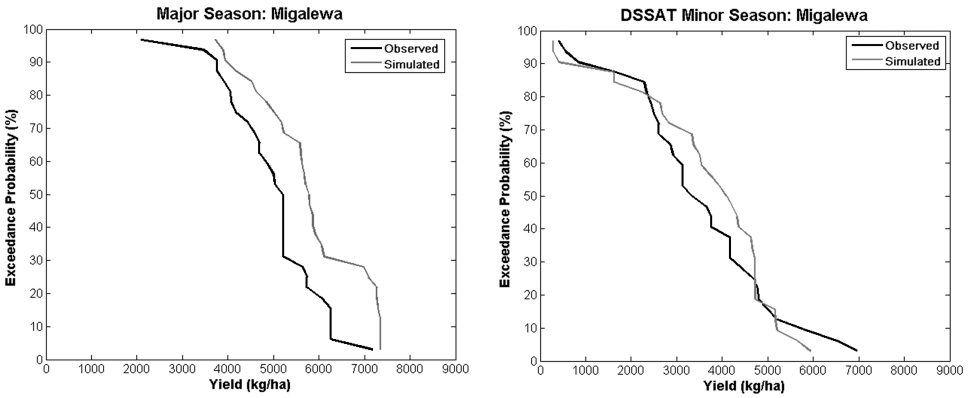


Fig. 9. The probability of exceedance of observed and simulated yields with DSSAT during the base year (2012–2013) in Migalewa for major and minor seasons.

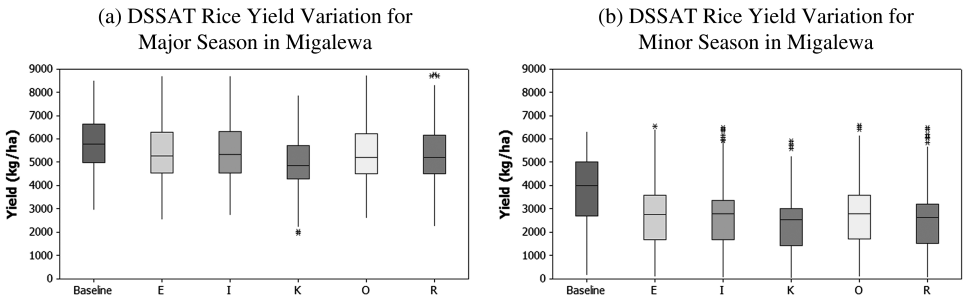


Fig. 10. DSSAT simulated rice yield for the major (A) and minor (B) seasons for five GCMs (mid-century) compared to baseline period for farmer fields Migalewa.

season were 3.1, 2.7, 9.8, 4.0, and 4.8%. The highest yield reductions were for simulations with GCM-HadGEM2-ES (Fig. 10).

Integrated Assessment Results

The results under Migalewa of Set 2 are presented under the integrated assessment section. The results from the TOA-MD analysis for Kadawaramulla are reported in Zubair *et al*. (2014) and Herath *et al*. (2013).

Addressing Core Question 1

With current agricultural systems and future climate: The projected climate change leads to a negative economic impact on 75–85% of farmers in Migalewa (Table 6). The percent of gains under all GCMs show similar results of approximately 13% of mean net returns. Net returns per farm decrease by 14–26% depending on the GCM

Table 6. TOA-MD analysis showing yields, net returns, *per capita* income, and poverty rate with and without climate change (top half labeled Question 1) and with climate change and changed agricultural practices (bottom half labeled Question 2) for Migalewa. The results are based on climate change as assessed from five selected GCMs CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR (labeled E, I, K, O, and R) and trends as in Group 1.

	Stratum	GCM				
		E	I	K	O	R
Question 1	Observed mean yield (Rice-Activity1-*Maha* season) (Kg/Ha/Season)	4985	4985	4985	4985	4985
	Mean yield change (Rice) (%)	−7	−6	−15	−8	−8
	Observed mean yield (Rice-Activity2-*Yala* season) (Kg/Ha/Season)	3508	3508	3508	3508	3508
	Mean yield change (Rice) (%)	−25	−27	−37	−25	−31
	Losers (%)	76	78	85	77	80
	Gains (% mean net returns)	13	12	13	12	13
	Losses (% mean net returns)	−24	−25	−32	−24	−27
	Observed net returns without climate change (Rs/Farm/Year)	115777	115777	115777	115777	115777
	Observed net returns with climate change (Rs/Farm/Year)	98630	96632	86290	97697	94200
	Observed *per capita* income without climate change (Rs/Person/Year)	54256	54256	54256	54256	54256
	Observed *per capita* income with climate change (Rs/Person/Year)	49939	49436	46833	49704	48824
	Observed poverty rate without climate change (%)	55	55	55	55	55
	Observed poverty rate with climate change (%)	60	60	63	60	61
Question 2	Projected mean yield (Rice-Activity1-*Maha* season) (Kg/Ha/Season)	5830	5830	5830	5830	5830
	Mean yield change (Rice) (%)	−7	−6	−15	−8	−8
	Projected mean yield (Rice-Activity2- *Yala* season) (Kg/Ha/Season)	5399	5399	5399	5399	5399
	Mean yield change (Rice) (%)	−25	−27	−37	−25	−31
	Losers (%)	77	79	88	75	82
	Gains (% mean net returns)	10	10	10	11	10
	Losses (% mean net returns)	−20	−21	−29	−20	−23
	Projected net returns without climate change (Rs/Farm/Year)	163224	163224	163224	163224	163224
	Projected net returns with climate change (Rs/Farm/Year)	141487	138993	123907	143477	135253
	Projected *per capita* income without climate change (Rs/Person/Year)	87778	87778	87778	87778	87778
	Projected *per capita* income with climate change (Rs/Person/Year)	81263	80516	75995	81860	79395
	Projected poverty rate without climate change (%)	28	28	28	28	28
	Projected poverty rate with climate change (%)	31	32	35	31	33

projection. The HADGCM-ES2 (identified by K) leads to the most significant losses and net impacts. Poverty rates increases by 8–15% for the five GCMs. Poverty line was defined as those earning less than $1.25/day. Highest poverty rate increase is shown under HADGCM-ES2 which has the highest temperature increase and the most yield drop. Note that the same rice prices are used for both System 1 and 2 with no trends used for yields and cost of cultivation. Hence analysis under Question 1 gives a basic assessment of the socio-economic impacts due to climate change.

Addressing Core Question 2

The impact of climate change on the future production system was assessed assuming that future production system will differ from current production system due to trends as described by the RAPs and the IMPACT global model and summarized in Group 1 in Table 5. The RAPs include an expectation of continuation of current development trends in the agriculture sector. The details of gains, losses, and net impacts are in Table 6 and in Fig. 11. We also assessed the sensitivity to the choices of RAPs by using trend factors (Group 2) taken largely from the IMPACT model.

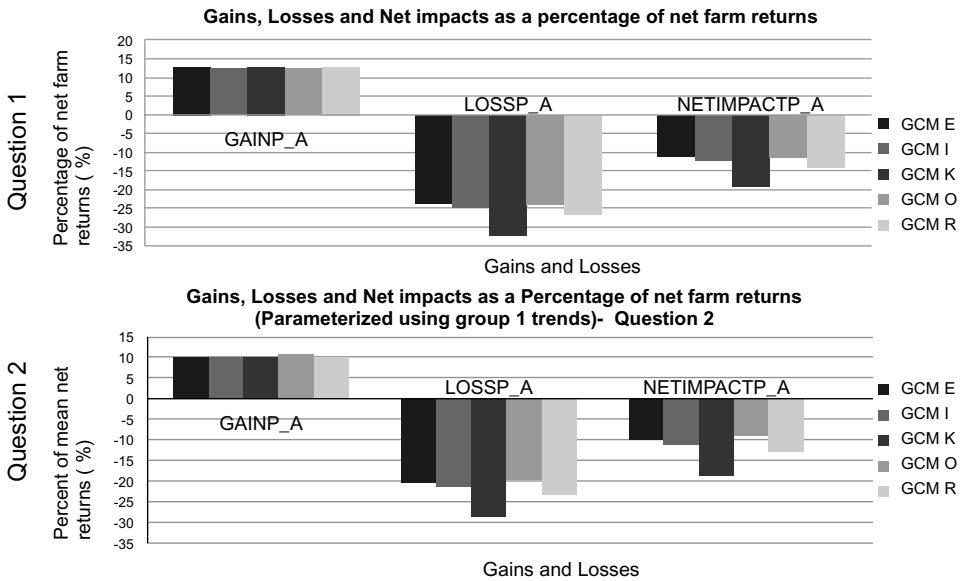


Fig. 11. The gains, losses and net impacts as a percentage of mean farm net returns for Migalewa as estimated by the TOA-MD analysis for Question 1 (top panel) of anticipated mid-century climate change and the current production system and Question 2 of anticipated mid-century climate change and future agricultural production system. The results are based on climate change as assessed inputs from five selected GCMs CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR (labeled E, I, K, O, and R).

Table 7. As in bottom half for Table 6, addressing the impacts of climate change with future agricultural production system as comparison of results anticipated by the factors as given in Group 1 and Group 2 (see Table 5).

	Group 1					Group 2				
Variables	GCM E	GCM I	GCM K	GCM O	GCM R	GCM E	GCM I	GCM K	GCM O	GCM R
Losers (%)	77	79	88	77	82	37	41	67	39	48
Projected net returns without climate change (Rs/Farm/Year)	163224	163224	163224	163224	163224	193637	193637	193637	193637	193637
Projected net returns with climate change (Rs/Farm/Year)	141487	138993	123907	143477	135253	204520	200880	179096	202745	195497
Percentage change in projected net returns (%)	−13	−15	−24	−12	−17	6	4	−8	5	1
Projected *per capita* income without climate change (Rs/Person/Year)	87778	87778	87778	87778	87778	96892	96892	96892	96892	96892
Projected *per capita* income with climate change (Rs/Person/Year)	81263	80516	75995	81860	79395	100154	99063	92535	99622	97450
Percentage change in *per capita* income (%)	−7	−8	−13	−7	−10	3	2	−4	3	1
Projected poverty rate without climate change (%)	28	28	28	28	28	23	23	23	23	23
Projected poverty rate with climate change (%)	31	32	35	31	33	22	22	25	22	23
Percentage change in poverty rate (%)	13	15	27	13	18	−7	−5	7	−6	−3

Climate change has a net negative economic impact on 76–88% of farmers with the future agricultural production system. The gains in the future under different GCMs range between 9.5 and 10% of mean farm returns (bottom left Fig. 11); losses range from 19 to 29% of mean farm returns). The losses under HADGCM-ES2 (GCM: K) are the highest. Net impact due to climate change would be negative for all GCM and losses shall range from 8–19% of net farm returns).

Poverty rate in the future production system without climate change is 27.8%. However poverty rates would increase with climate change by 12–26%. Poverty rates and *per capita* incomes under Question 2 have decreased in comparison to Question 1 (without climate change). The increase in off-farm income by 30% as anticipated under the RAPs has caused this decrease. The decrease in household sizes (by 16%) has also contributed to bringing down poverty rates.

Sensitivity analysis

To address the sensitivity of the TOA-MD results to the choice of future trends in the RAPs, we have redone the analysis with a different set of growth factors obtained mostly from the global IMPACT economic model (Group 2 in Table 5). Between Group 1 and 2, the trends for global prices, household size, farm area, and non-agricultural income were identical. There were significant differences in the trends for yield, local prices, and cost of production with the values in Group 2 being approximately about 15–20% greater. The results are shown in Table 7 and

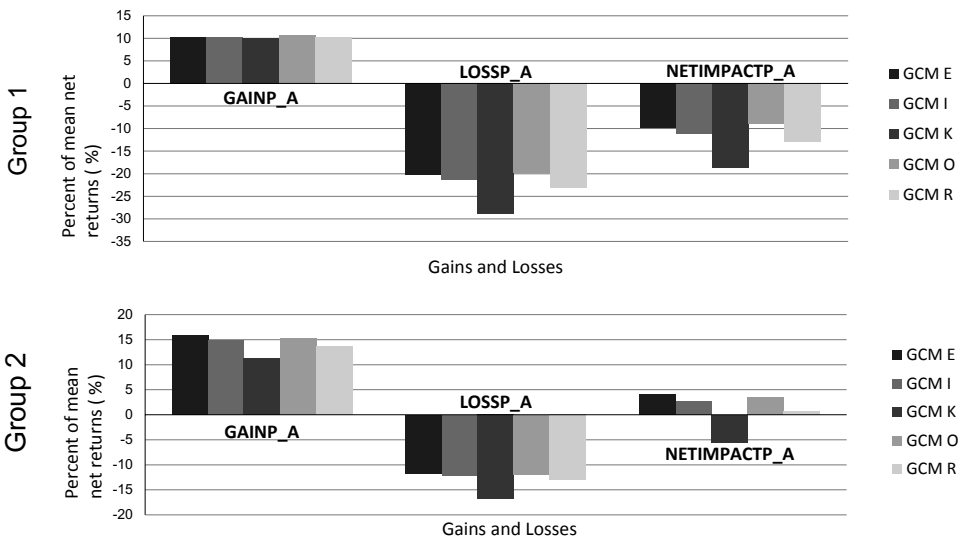


Fig. 12. Variation of gains, losses, and net impacts as a percentage of net farm returns for Question 2 utilizing Group 1 and 2 trends.

Fig. 12. Using the Group 2 trend values, the change in projected returns under climate change were actually more positive for four GCMs in contrast to the results with Group 1. Similarly the percentage change in *per capita* income was favorable for four GCMs under climate change, again in contrast to the results with trend factors from Group 1. These results show that the trend factors for yield, local prices and cost of production are critical. They also show the high sensitivity of the results to the input trend factors. Moreover the percentage of vulnerable farms (% of losers) is much lower under the Group 2 analysis compared to Group 1. This provides a confirmation that the choice of trend factors from global economic models and RAPs are likely to be one of the vital key elements in the process of designing adaptation strategies.

Conclusions and Discussion

A sustained program of research under AgMIP has led to the implementation of climate, crop, and economic models of rice agricultural systems in Sri Lanka.

Conclusions

Climate

The climate projections show a clear increase in temperature in the mid-20th century for a high greenhouse gas concentration pathway (RCP8.5); these models show a tendency towards a wetter future but there is scatter in these results. The results were largely consistent across five locations in Sri Lanka and the details are provided for data from the northwestern Province. The changes in the model output are described in terms of the Maha and Yala seasons next. The increase in average temperature for 2040–2070 from that of 1980–2010 ranged from 1.1–2.4°C for Maha and 1.5–2.8°C for Yala seasons. The rainfall shows a slight increase for a preponderance of the 20 GCMs in the CMIP5 archive, with the highest increase for October–November. During Maha, the average rainfall rises from a present average of 6 mm/day up to a future 9.5 mm/day for 19 of the models while it drops by 0.1 mm/day for one model. The magnitude of the rise was statistically significant for 16 of these models. During the Yala season, half of the models showed a decline in average rainfall of up to 1 mm/day from the normal of 2 mm/day, including four of five selected GCM outputs and 10 of the other models showed an increase — this increase was statistically significant for these ten models.

Crop

Genetic coefficients for the DSSAT and APSIM rice models, which were generated with Set 1 data, are presented here. Genetic coefficients obtained independently with a subset of data are presented in Zubair *et al*. (2014) and are similar.

Simulations were undertaken for farmer fields with Set 1 and Set 2 of data with DSSAT and APSIM rice models and the DSSAT results are presented for both sets. These simulations showed an adequate match of the probability of exceedance in the case of DSSAT for both sets while the estimates from the APSIM models were lower.

Under the projected climate change, the simulations using DSSAT with climate change scenarios projected relative yields that were lower for the Maha season (by 6–19% for Set 1 and 6–15% for Set 2) and for the Yala season (24–41% for Set 1 and 25–37% for Set 2).

Crop simulations from DSSAT and APSIM with Set 1 showed contrasting results. The comparison of simulated and observed yields for the farmer fields in Set 1 showed a lower RMSE with DSSAT than APSIM for Maha but not for Yala. Simulated yields showed yield drops for the future- 12–19% for Maha and 27–41% for Yala.

The adverse effects were more pronounced for the Yala season. The GCM with the highest temperature increase — HadGEM2-ES — showed the highest yield drop — 41% for Yala.

Integrated assessment

The TOA-MD economic model was used to assess the socio-economic impacts on paddy farmers due to climate change. The projected climate change brings losses for most farmers (ranging from 75–85% losers depending on the GCMs) for Migalewa. TOA-MD results for the GCM with the highest temperature increase (HadGEM2-ES) showed the lowest yields and highest economic impacts with 85% losers.

The impact of climate change on the future production system was assessed (Question 2) assuming that future production system will differ from current production system due to continuation of current development trends in the agriculture sector. Considering such trends along with climate change leads to a simulated 77–88% losers in Migalewa.

The results were sensitive to the choices in parameter trends obtained from the RAPs and the ones obtained from IMPACT. This has important implications for the design and implementation of policies and adaptation strategies based on the analysis of possible future impacts of climate change. More work is needed to understand better the effects of technology and price trends as a result of global economic models or other projections.

Discussion

Climate

The future projections for temperature reported here are consistent with past IPCC projections for South Asia (IPCC, 2007). The IPCC Fifth Assessment Report (AR5)

anticipates an increase in temperature of 2.4 to 2.6°C in the global average for RCP2.6 for 2046–2065 and an increase in annual rainfall of up to 10% for 2081–2100 (IPCC, 2013).

There has been a multiplicity of downscaled climate projections for Sri Lanka based on assessments prior to AR5 which was reviewed by Eriyagama and Smakthin, (2010). These projections agree reasonably among themselves on projections for temperature and disagree widely among themselves for projections of precipitation. The contribution of this work is to undertake assessments with the entire ensemble of CMIP5 models and present the ensemble of results, which also includes uncertainty among model implementations.

While this work provides for uncertainty among the climate models, we do need to address the larger issue of how well the models perform in this region, the small spatial scales that we consider, and the robustness of the models as they take on different regimes in the climate system. The climate models as implemented also do not provide a basis for future changes in extreme events. These are issues that could be better answered in the future and should be considered in the interpretation of implications for policymaking.

In the recent decades, there has been a tendency towards drying conditions in the study region and in Sri Lanka generally. Such a trend has not been captured by models in the past. This phenomenon of near-term climate change needs to be addressed in the future. Thus the paradox of the recent drying trend alongside projections of wettening needs to be addressed.

Crop

We have assessed the sensitivity of rice yield with temperature, CO_2, and rainfall by varying each of these parameters individually in the anticipated range of changes with a DSSAT crop model implementation with Set 1 (Zubair *et al*., 2014). The model shows very little sensitivity to changes in rainfall by, and modest sensitivity to CO_2, but high sensitivity to changes in temperature. These results are consistent with past work that shows that rice yields are expected to increase with elevated CO_2 levels and decline with increases in temperature (Wassmann and Dobermann, 2007) but provide specific quantitative details for our model implementation in Zubair *et al*. (2014).

The effects of pests and diseases on paddy production can override some of the projections and thus need to be taken account of in the future. The role of rising salinity will have to be considered in the coastal areas that are vulnerable to salt water intrusion into groundwater associated with sea level rise.

There is a need to implement modules and test their implementation to take better account of water stress in the rice crop models as we use these models for relatively drier areas with limited irrigation in Sri Lanka.

There is a range of climates even within the rice-growing areas of Sri Lanka, which includes warmer, colder, drier, and wetter climates, and other soil types and associated agricultural practices for which the crop models should be further tested. One could also take advantage of practices in locations that may have a present climate similar to a projected future climate elsewhere.

Integrated assessment

In the RAPs that we used, the future agricultural practices help improve rice productivity trends and help mitigate the negative impacts of climate change on agricultural systems. Any RAP is only representative and other choices should be considered. The results from the TOA-MD model are highly dependent on the crop model simulations and on model implementation.

Any biases in the crop simulations would affect the TOA-MD results significantly. The samples used to parameterize the model are fairly small under this study. In the future, the crop and economic models shall be implemented for other sites where we already have survey results.

Our analysis points to the likelihood of inadequate income stability of farming and this can cause farmers to look for other employment options. Increase in off-farm employment under the RAP could have been one of the factors leading to this outcome. However this could pose a serious threat to rice production and will need to be addressed.

An aggregate study (Seo *et al*., 2005) to assess climate change impacts on agriculture in Sri Lanka show that impacts due to climate change could vary from −11 billion rupees to +39 billion rupees nationally depending on the climate scenario (Seo *et al.*, 2005). This work has provided for economic impacts on a much finer scale, taking better account of local conditions. Although one may say that there is general agreement with our work, the state of such studies are preliminary and highly dependent on future projections, methodology, and future agricultural pathways.

Adaptation measures

The adaptation strategies that were described in the first section of this chapter are aimed to deal with three important issues. Coping with extreme risks for farmers, varietal improvement, and coping with water scarcity. An extension to the current analysis will be to assess the impacts of those adaptation strategies on the agricultural production system of Migalawa.

Farmer risk reduction and risk transfer

Both our surveys of farmers and work with the economic analysis highlighted the need for better management of risks that farmers face. Better weather- and

climate-based hazard predictions, predictions for water availability, market-based risk predictions, the use of risk transfer mechanisms such as insurance and farming cooperatives, and better implementation of guaranteed price schemes shall have to be prioritized if there is a policy priority for sustaining the number of rice farmers in Sri Lanka.

Changes in varietal use and varietal improvement

There is significant variation of climate in Sri Lanka and agricultural practices. Thus as climate changes it may still be possible that varieties adapted to other regions become better suited for a given region. Such an analysis of climate shall point to some options for varietal adoption. Further analysis of data from varietal trials may help. In addition, there is an ongoing program of varietal improvement in Sri Lanka which may be critical as climate changes. The adoption of varieties that have enhanced flood, drought, salinity, and disease tolerance as the climate and soil conditions change may be critical to tolerant rice varieties.

Water management

Our work here has been with assumptions of perfect irrigation. However as seen in Kadawaramulla, drought and irrigation failures are critical. Moreover, there is increasing likelihood of diversion of water for urban use and other purposes (Zubair *et al*., 2014). Thus greater attention shall have to be paid to assessing the risk of water scarcity in the future in agricultural areas, the risks in ensuring adequate irrigation, and the use of water conservation techniques.

Acknowledgements

We are grateful to the AgMIP leaders, AgMIP experts in crop, climate, and economic models, and others who helped with coordinating this work, in presentation and in document preparation. We would like to thank Kenneth Boote and Alexander Ruane, among others, for helping with their detailed and helpful review of the chapter drafts. Use of data from the Departments of Agriculture Meteorology and Census and Statistics and the Mahaweli Authority are gratefully acknowledged. We are grateful to the farmers who have helped us understand their practices patiently and the farmer organization leaders, extension workers, and other officials who facilitated access to the farmers. We are also grateful to the other team members who enabled this work but are not listed as authors here.

References

Amarasinghe, U. A., Mutuwatta L., and Sakthivadivel, R. (1999). Water scarcity variations within a country: a case study of Sri Lanka, International Water Management Institute, Research Report 32, Colombo, Sri Lanka.

Antle, J. M. (2011). Parsimonious Multi-Dimensional Impact Assessment, *American Journal of Agricultural Economics*, **93**(5), 1292–1311.

Antle, J. M. and Valdivia, R. O. (2006). Modelling the supply of ecosystem services from agriculture: A minimum-data approach, *Australian Journal of Agricultural and Resource Economics*, **50**, 1–15.

Central Bank of Sri Lanka (2013). *Economic and Social Statistics of Sri Lanka*, Central Bank, Colombo, Sri Lanka

Climate Change Secretariat (2010). *National Climate Change Adaptation Strategy for Sri Lanka 2011 to 2016*, Climate Change Secretariat, Sri Lanka Ministry of Environment, Colombo.

De Costa, W. A. J. M., Weerakoon, W. M. W., Chinthaka, K. G. R., Herath, H. M. L. K., and Abeywardena, R. M. I. (2007). Genotypic variation in the response of rice (Oryza sativa L.) to increased atmospheric carbon dioxide and its physiological basis, *Journal of Agronomy and Crop Science*, **193**(2), 117–130.

Department of Agriculture (2009). *Paddy Statistics of Sri Lanka*, Department of Agriculture Press, Gannoruwa, Sri Lanka.

Department of Agriculture (2010). *Agriculture Statistics of Sri Lanka*, Department of Census and Statistics, Department of Agriculture Press, Gannoruwa, Sri Lanka.

Department of Census and Statistics. (2012a). *Small Holding Sector. Census of Agriculture-2002*, Department of Census and Statistics Press, Colombo, Sri Lanka.

Department of Census and Statistics (2012b). *Census of Population and Housing*, Department of Census and Statistics Press, Colombo, Sri Lanka.

Dharmarathna, W. R. S. S., Herath, S., and Weerakoon, S. B. (2014). Changing the planting date as a climate change adaptation strategy for rice production in Kurunegala district, Sri Lanka, *Sustainability Science*, **9**(1), 103–111.

Eriyagama, N. and Smakhtin, V. (2010). "Observed and Projected Climatic Changes, Their Impacts and Adaptation Options for Sri Lanka: A Review", in *Proceedings of the National Conference on Water, Food Security and Climate Change in Sri Lanka*, Volume 2, International Water Management Institute, Colombo pp. 99–117.

Gadgil, S., Rajeevan, M., Zubair, L.. and Yadav P. (2011). "South Asian Monsoon: Inter Annual Variability", in Chang, C., Ding, Y., Lau, N., Johnson, R. H., Wang, B., and Yasunari, T. (eds.), *Global Monsoon System, Research and Forecast*, World Scientific Publishing Company, Singapore.

Herath, D., De Alwis, A. E. N., Agalawatte, A. S. M. P. M. B., Harischandra, Y. G., Chandrasekara, S. S. K., Yahiya, Z., Zubair, L., and Samaratunga, P. A. (2013). "Simulating Socio Economic Impacts of Climate change on Rice Farming Systems: Trialing a Novel Integrated Methodology for Kadawaramulla, Kurunegala", in *Proceedings of the University of Peradeniya Economics Research Symposium (PERS) 2013*, University of Peradeniya, pp. 38–42.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas, *International Journal of Climatology*, **25**, 1965–1978.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

IPCC (2007). Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L. (eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC*, Cambridge University Press, Cambridge.

IPCC (2013). Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. (eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, p. 1535.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**(3), 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silbum, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCron, R. L., Freebairn, D. M., and Smith, C. J . (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**(3) 267–288.

Kurukulasuriya, P. and Ajwad, M. I. (2007). Application of the Ricardian technique to estimate the impact of climate change on smallholder farming in Sri Lanka, *Climatic Change*, **81**(1), 39–59.

Lyon, B., Zubair, L., Ralapanawe, V., and Yahiya, Z. (2009). Fine scale evaluation of drought hazard for tropical climates, *Journal of Applied Meteorology and Climatology*, **48**(1), 77–88.

Mahanama, S. P. P. and Zubair, L. (2011). Production of streamflow estimates for the Climate Change Impacts on Seasonally and Intermittently Open Tidal inlets (CC-SIOT) Project, FECT Technical Report 2011-01, Foundation for Environment, Climate and Technology, Digana Village.

Mapa R. B., Dassanayake A. R., and Nayakekorale, H. B. (2005). Soils of the Intermediate Zone of Sri Lanka: Morphology, Characterization and Classification, Special publication No. 4, Soil Science Society of Sri Lanka, Peradeniya.

Matthews, R. and Wassmann, R. (2003). Modelling the impacts of climate change and methane emission reductions on rice production: A review, *European Journal of Agronomy*, **19**(4), 573–598.

Ministry of Agricultural Development and Agrarian Services (2008). "Let us cultivate and uplift the nation", National campaign to motivate domestic food production 2008–2010, Ministry of Agricultural Development and Agrarian Services of Sri Lanka, Colombo.

Ministry of Agriculture Development and Agrarian Services. (2007). *National Agricultural policy for Sri Lanka*. Available at: http://www.agrimin.gov.lk/web/images/docs/1277294350E%20NATIONAL%20AGRICULTURAL%20POLICY.pdf. Accessed on 28 September 2014.

Ministry of Environment (2000). *National Report on Desertification/Land Degradation in Sri Lanka*. Available at http://www.unccd.int/regionalreports/sri_lanka-eng2000.pdf. Accessed on 28 February 2014.

Climate Change Secretariat (2010). *National climate change adaptation strategy for Sri Lanka. 2011–2016*, Climate Change Secretariat, Ministry of Environment, Colombo, Sri Lanka.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks. T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

Pain, A. (1986). "Agricultural Research in Sri Lanka: An Historical Account", in *Modern Asian Studies*, Cambridge University Press, Cambridge, **20**(4):755–778.

Punyawardena, B. V. R. and De Silva, R. P. (2011). *Drought Risk Profile of Sri Lanka*, Disaster Management Center, Sri Lanka.

Raby, N. and Merrey, D. (1989). *Professional Management in Irrigation Systems: A Case Study of Performance Control in Mahaweli System H Sri Lanka*. Available at: http://pdf.usaid.gov/pdf_docs/PNABG169.pdf. Accessed on 19 October 2014.

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M.G., Schubert, S. D., Takacs, L., Kim, G. K., Bloom, S., Chen, J. Y., Collins, D., Conaty, A., da Silva, A., Gu, W., Joiner, J., Koster, R. D., Lucchesi, R., Molod, A., Owens, T., Pawson, S., Pegion, P., Redder, C. R., Reichle, R., Robertson, F. R., Ruddick, A. G., Sienkiewicz, M., and Woollen, J. (2011). MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, *J. Clim.*, **24**(14), 3624–3648.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Mutter, C. Z., Adiku, S. G. K., Ahmad, A., Beletse, Y., Gangwar, B., Guntuku, D., Kihara, J., Masikati, P., Paramasivan, P., Rao, K. P. C., and Zubair, L. (2012). "The Agricultural Model Intercomparison and Improvement Project (AgMIP): Integrated regional assessment projects", in Hillel, D. and Rosenzweig, C. (eds.), *Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications*, Imperial College Press, London, pp. 263–280.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Antle, J. M., Boote, K. J., Thorburn, P., and Valdivia, R. O. (2013a). *AgMIP Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.1*. Available at: http://www.agmip.org/wp-content/uploads/2014/07/AgMIP-Regional-Integrated-Assessment-Handbook-v5.1.pdf. Accessed on 21 March 2014.

Rosenzweig, C., Jones, J. W., Hatfield, J. L, Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C, Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013b). Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Ruane, A. C., Goldberg, R. and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol.*, 200. doi: 10.1016/j.agr.formet.2014.09.016.

Samuel, T. D. M. A. (1991). Estimation of global radiation for Sri Lanka, *Solar Energy*, **47**, 333–337.

Sangakkara, U. R. and Nissanka, S. P. (2008). Food security in Sri Lanka — Agronomic Implications and Potentials, *Journal of National Science Foundation Sri Lanka*, **36**(2), 17–24.

Seo, S. N. N., Mendelsohn, R., and Munasinghe, M. (2005). Climate change and agriculture in Sri Lanka: A Ricardian valuation, *Environment and Development Economics*, **10**, 581–596.

Taylor, K. E., Stouffer, R. J., and Gerald, A. M. (2012). An overview of CMIP5 and the experiment design, *Bulletin of the American Meteorological Society*, **93**(4), 485–498.

Wassmann, R. and Dobermann, A. (2007). Climate change adaptation through rice production in regions with high poverty levels, *Journal of Semi-Arid Tropical Agricultural Research*, **4**(1).

Weerakoon, W. M. W., De Costa, W. A. J. M., and Abeysiriwardena, D. S. de Z. (2005). Physiological responses of indica rice varieties to increased atmospheric CO_2 and temperature, *Journal of Agricultural Meteorology*, **60**, 601–604.

Wickremasinghe, S. T. (2006). Development of the national agricultural research system (NARS) in Sri Lanka with special reference to food crops sub sector: Issues related to science policy, *Journal of National Science Foundation Sri Lanka*, **34**(2), 69–83.

Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. O. (2004). *Guidelines for use of climate scenarios developed from statistical downscaling methods*. Available at: http://www.narccap.ucar.edu/doc/tgica-guidance-2004.pdf. Accessed on 14 October 2014.

Yahiya, Z., Adhikari, S., Weerasekara, M., and Zubair, L. (2011). The Impacts of El Nino Southern Oscillation (ENSO) Events on Rice Production, Area and Yield in Sri Lanka, FAO/SEARCA Project. FECT Technical Report 2010-01, Foundation for Environment, Climate and Technology, Digana Village.

Zubair, L. (2002). El-Nino-Southern Oscillation influences on Rice Production in Sri Lanka, *International Journal of Climatology*, **22**, 249–260

Zubair, L. (2004). *Weather and Climate in Sri Lanka: A Reference Guide*, Natural Resources Management Services, Kandy, Sri Lanka.

Zubair, L. (2005). Modernization of Sri Lanka's Traditional Irrigation System and Sustainability, *Science, Technology and Society*, **10**(20), 161–195.

Zubair, L., R. Perera and Z. Yahiya. (2005). Was the 2002/03 Maha bumper harvest due to El Nino?, *Journal of the Institute of Engineers*, **4**, 63–70.

Zubair, L. and C.F. Ropelewski. (2006). The strengthening relationship of ENSO and the North-East Monsoon rainfall over Sri Lanka and Southern India, *Journal of Climate*, **19**(8), 1567.

Zubair, L., Nissanka, S. P., Weerasinghe, K. D. N., Punyawardhene, B. V. R., Weerakoon, W. M. W., Wickramagamage, P., Agalawatte, P., Chandrasekera, S. C., Delpitiya, P., Navaratne, C. M., Gunaratna, J., Herath, D. I., Herath, R. M., Karunaratne, A., Ratnayake, S., Samaratunga, P., Sanmuganathan, K., Vishwanathan, J., Wijekoon, E., Weerasinghe, A. K., Yahiya, Z., Perera, T. M. R. S., Gunesekara, A. A. I., Ratnasekera, H., Ralapanawe, V., Seneviratne, G., and Wallach, D. (2014). Modeling the impacts of a variable and changing climate on rice agricultural systems in Sri Lanka for AgMIP. Sri Lanka Project Final Report for AgMIP, Technical Report, Foundation for Environment, Climate and Technology, Kandy, Sri Lanka.

Section III

Other AgMIP Regions

This page intentionally left blank

Chapter 11

AgMIP Regional Activities in a Global Framework: The Brazil Experience

Eduardo D. Assad[1], Fábio R. Marin[2] , Roberto O. Valdivia[3], and Cynthia Rosenzweig[4]

[1]*Brazilian Agricultural Research Corporation, São Paulo, Brazil*

[2]*Universidade de São Paulo, São Paulo, Brazil*

[3]*Oregon State University, Corvallis OR, USA*

[4]*NASA Goddard Institute for Space Studies, New York, NY USA*

Introduction

Climate variability and change are projected to increase the frequency of extreme high-temperature events, floods, and droughts, which can lead to subsequent changes in soil moisture in many locations (Alexandrov and Hoogenboom, 2000). In Brazil, observations reveal a tendency for increasing frequency of extreme rainfall events particularly in south Brazil (Alexander *et al*., 2006; Carvalho *et al.*, 2014; Groissman *et al*., 2005), as well as projections for increasing extremes in both maximum and minimum temperatures and high spatial variability for rainfall under the IPCC SRES A2 and B2 scenarios (Marengo *et al.*, 2009).

Agribusiness is responsible for about 30% of the Brazilian economy and is a critical contributing sector for economic growth and foreign exchange. Agriculture accounted for about 23% of GDP and 27% of Brazilian exports in 2013. In 2013 Brazil showed a positive agricultural trade balance of US $ 99.97 billion USD (MAPA, 2014) Brazil is the world's largest producer of sugarcane, coffee, tropical fruits, and frozen concentrated orange juice. It has the world's largest commercial cattle herd (50% larger than that of the USA) at 210 million head. Brazil is also an important producer of soybeans (second only to the United States), as well as maize, cotton, cocoa, tobacco, and forest products. The remainder of agricultural output is

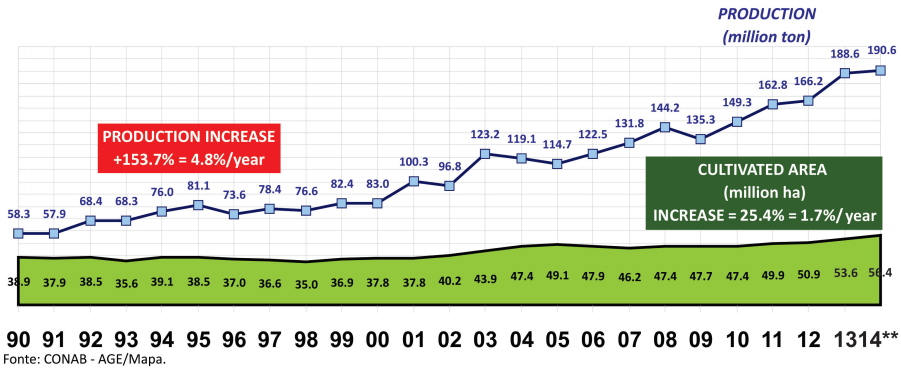


Fig. 1. Grain production and area increase in Brazil from 1991–2013.
Source: http://www.conab.gov.br/conteudos.php?a=1252&t=2.** 2014 (estimated).

in the livestock sector, mainly the production of beef and poultry, pork, milk, and fish.

Between 1996 and 2013, the total value of Brazil's crops rose from US $12 billion to US $330 billion. Brazil increased its beef exports tenfold in a decade, overtaking Australia as the world's largest exporter. It is also the world's largest exporter of poultry, sugarcane, and ethanol. Since 1990, national soybean production has risen from less than 15 million tons per year to over 60 million tons. Brazil accounts for about a third of world soybean exports. In 1994, Brazil's soybean exports were one seventh of the USA's; now they are six sevenths. Moreover, Brazil supplies a quarter of the world's soybean trade on just 6% of the country's arable land. From 1991 to 2010, the grain production of the country (cotton, peanut, rice, bean, sunflower, corn, soybean, sorghum, wheat, oat, barley, castor bean, rye, and rapeseed) increased by 147%, while cultivated area increased only 25%; or 4.8%/year and 1.7%/year respectively (Fig. 1). This was due to major development in agricultural technology.

These statistics highlight the importance of agriculture for the country's economy, as well as the challenges faced by Brazil related to projected climate change impacts on the agricultural sector. During the last decade, intense interest has been focused on what and how research strategies could help Brazilian agriculture to cope with climate change. The philosophy and protocols of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig *et al.*, 2013), have converged with these discussions. Since 2009, Brazil has implemented a national climate change policy, with emphasis on energy, agriculture, industry, and especially on the great effort to reduce deforestation in the Amazon region. In terms of mitigation of greenhouse gases, a set of the national actions was defined. In the agriculture sector, a policy of low carbon emissions was adapted, whereby emissions should be reduced by 30% by the year 2020 through the adoption of appropriate agricultural

practices. The next principal challenge is the identification of possible adaptations to high temperature, reduction of rainfall, and increased CO_2

In order to relate the Brazil experience under the AgMIP framework (Rosenzweig *et al*., 2013), we analyzed the impacts of climate change on agriculture and the environment based on two main aspects. The first one involves the agricultural sector as a whole, as it is expected that Brazil will play a significant role in global food security in the coming decades. Indeed, the OECD/FAO joint report "Agricultural Outlook 2012" (OECD/FAO, 2012) estimates that agricultural production needs to increase by 60% over the next 40 years to meet rising demand for food. Additional production will be necessary to provide raw material for bio-fuel and non-food agricultural products, including cotton, timber wood, and cellulose paste. Most of this additional supply is expected to come from developing countries and emerging economies, with a sizeable share from Brazil. In fact, Brazil still has a large stock of agricultural land available to be brought into sustainable cultivation by entrepreneurial local farmers, and in the last three decades local research-and-development institutions have mastered technology for tropical agriculture. However, this positive outlook should be balanced by several factors, including deficits in infrastructure, institutional risks, and, in particular, the uncertainties associated with climate change.

Brazilian agriculture is moving from subtropical regions of the south to the tropical areas of the Brazilian Savannahs in the midwest and northwest, where production is mainly rainfed. In spite of technological progress, which is responsible for nearly 75% of increased output in the last 20 years (Gasques *et al.*, 2012), the total factor of productivity is still largely dependent on the rainfall regime, notably the quantity, distribution, and frequency of rains and dry spells throughout the seasons (Carvalho *et al.*, 2013). Rainfall regimes are rapidly changing and will be further affected by climate change in the near future. This could have an impact on both local welfare and world food production. In considering the impacts on local welfare, one should note that farming in Brazil is neither an enclave activity (as it had been in the past) nor itinerant (as depicted by the misleading image of tropical farming as a slash-and-burn practice that leaves only ashes behind after a few years of high yields provided by unsustainable exploitation of natural resources).

The agriculture established in the frontier regions of the midwest, north, and northwest has occupied undeveloped land, created many cities where millions of Brazilians now live, and engaged many in activities that are mostly associated with agricultural production and agribusiness. Some questions should be raised to guide planning in this regard: What is the expected impact of climate change on Brazilian agriculture, particularly on tropical agriculture that is currently responsible for the booming Brazilian agribusiness? What are the possible consequences regarding the ability to feed the world and, in particular, the Brazilian population? This is

a dimension we explore by using data from EMBRAPA (Brazilian Agricultural Research Corporation), which has good indicators and rigorous studies by which we can do a critical review.

The second aspect for which we analyzed the impacts of climate change on agriculture and the environment relates to the desertification of Brazil's northeast semi-arid region, which has the highest population density of any semi-arid region in the world (Assad *et al*., 2013). The northeast, and its semi-arid region in particular, is the poorest part of the country, with the largest poor population in Latin America. The Brazilian semi-arid region is characterized by large social inequalities and massive poverty. According to Assad *et al*. (2012), 58% of the Brazilian poor live in the semi-arid region and more than 70% of the semi-arid region population lives in poverty or extreme poverty conditions. Among 1,133 municipalities, many have a low human development index (HDI) and only reach national average values of HDI. The process of desertification is also underway, and could accelerate with climate change (Assad *et al*., 2013). In 2012, the region had experienced the third successive year of drought, with severe social impacts. The problem of desertification in the northeast is not new, but it is getting worse. This issue is explored in this chapter, through observed data and climate change projections with a critical review of the debate and with presentation of strategies and policies for responding to ongoing desertification and climate change.

Brazilian Agricultural Climatic Risk Zones and Climate Change Impacts

A coordinated effort that helps to organize agroclimatic activities in Brazil is the Brazilian Agricultural Climatic Risk Zones Project, which was started by the Ministry of Agriculture of Brazil in the early 1990s and still guides agricultural development in the country. The initiative is based on the understanding that the agroclimatic potential of such regions may be established based on parameters that define temperature and soil water regimes appropriate for specific crops.

Deciding what, when, and where a crop should be sown, for a certain risk level, is a direct function of weather in the plant cycle. The process of creating agricultural climatic risk zones integrates simulation models of crop growth based on data from climate, soil, and phenological characteristics of the crop, as well as techniques of geographic information systems (GIS) and decision analysis.

In Brazil, the official risk zones have been public policy since 1996. For each of the 5,564 municipalities of the country, crop suitability is defined for planting with less than 20% risk of economic success in the harvest. These statements are made based on the phenology of each cropping system, by considering the negative effects of excess water, drought, or extreme temperatures in the critical phases of the plant. Lack of water during grain-filling can damage a crop of maize or soybeans.

Excessive rain at harvest time can impair the quality of the grains. The incidence of extreme temperatures can cause loss of production due to flower abortion in the case of high temperatures or frost damage by low temperatures.

In 2001, EMBRAPA and UNICAMP (State University of Campinas) developed a system to simulate the different conditions of climate and soil for application to risk zonation of agricultural crops. The results obtained created a basis for a near-complete knowledge of the agricultural geography of Brazil.

The zonation of climatic hazards developed by EMBRAPA and UNICAMP, in collaboration with other research institutions in Brazil, assesses the suitability of a particular region to a particular type of crop, not only with weather data (rainfall and temperature), but also with specific indices developed to characterize the sensitivity of the crops to extreme events that may occur during critical phenological stages. The use of GIS and satellite images is essential in this process. With this information, it is possible to show the likelihood of obtaining yields with at least minimal economic productivity. Moreover, the evolution of climate modeling, with resulting projections of future climate scenarios due to global climate change, enables projections of the redistribution of crops according to the rising temperatures. In this case, the methodology is similar to the risk zonation, with the difference that it also takes into account other factors such as increased evapotranspiration and moisture deficit or surplus due to high temperature (Fig. 2).

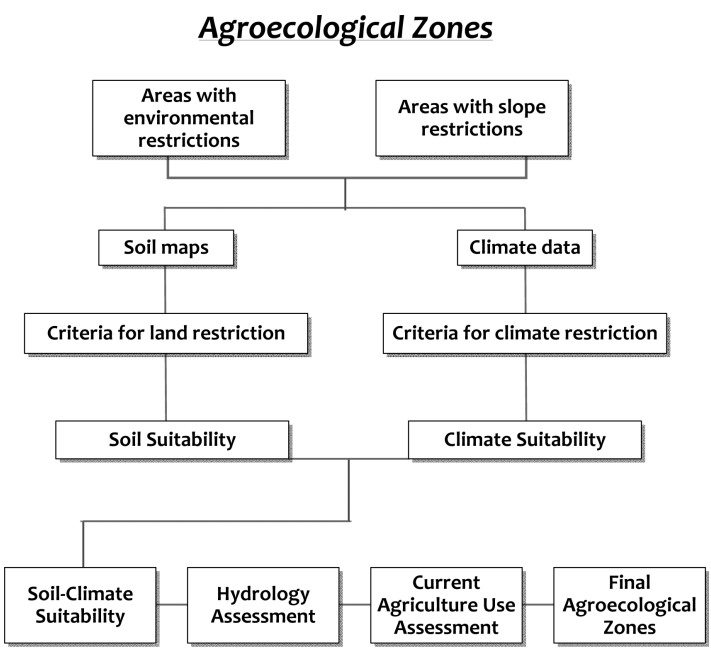


Fig. 2. Flowchart of agroecological zones methodology.

This methodology was adapted from the agroecological zones methodology developed by Food and Agriculture Organization. It has been used for studies of bioenergy products and rice in Brazil (Monteiro *et al*., 2013). The data are processed to calculate potential evapotranspiration (PET) and crop water requirements (ISNA, indice de satisfação de necessidade de água), which are defined as:

- Potential evapotranspiration (PET), according to Thornthwaite and Mather (adapted after correction by Penman evapotranspiration methods), is an estimate of water evaporation from the soil and transpiration by plants at full capacity, with the soil completely covered by grass and there is an optimal supply of water in the root zone. In this study, the PET is calculated as a function of temperature, according to the method of Camargo and Camargo (1983).
- ISNA can be considered as the rainfall requirement of the crop and is expressed in terms of millimeters and is similar to crop water-stress index.

To assess the availability of soil water during the critical phases of crop growth, we used the concept of ISNA, represented by the relationship between actual evapotranspiration and the potential evapotranspiration (RET/MET; real evapotranspiration divided by maximum evapotranspiration). The values normally used are around 0.60 (Zullo *et al*., 2006). This concept allows the estimation of probabilities of occurrence of phenomena that affect crop water productivity.

The principle for determining the type of climate risk is simple. The areas of lowest risk are those where there is sufficient water to guarantee germination and, especially, flowering and grain-filling, which comprise the important phenological stages affecting the productivity of crops. This risk is set not to exceed 20%. In the case of global climate change, the increase of MET reduces ISNA, which thereby increases climate risk. In the case of agricultural zonation of climatic hazards, the method was adopted for most grain crops, as they are short-cycle annuals.

To define the risk, agrometeorological indices are calculated from crop evapotranspiration, which is the sum of leaf transpiration and soil evaporation. It can also be defined as the total amount of water lost from a surface covered with vegetation through direct evaporation of water from crop interception and the soil surface. Each crop has its optimum water requirement, regulated for photosynthesis, which depends directly on the amount of water available and air temperature. When these conditions are met, planting is recommended. By these criteria, one can delineate the area in which any crop can be produced in Brazil and the associated risks. After mapping the potential crop areas, we then introduce climate change scenarios for future years, i.e., 2020s, 2030s, and 2040s (Assad *et al.,* 2013). Figure 3 shows the flowchart for calculating the climatic risk for grains.

Finally, when the climatic suitability zonation is calculated, the thermal limits are considered as well as the stressing incurred by crops. In this particular case,

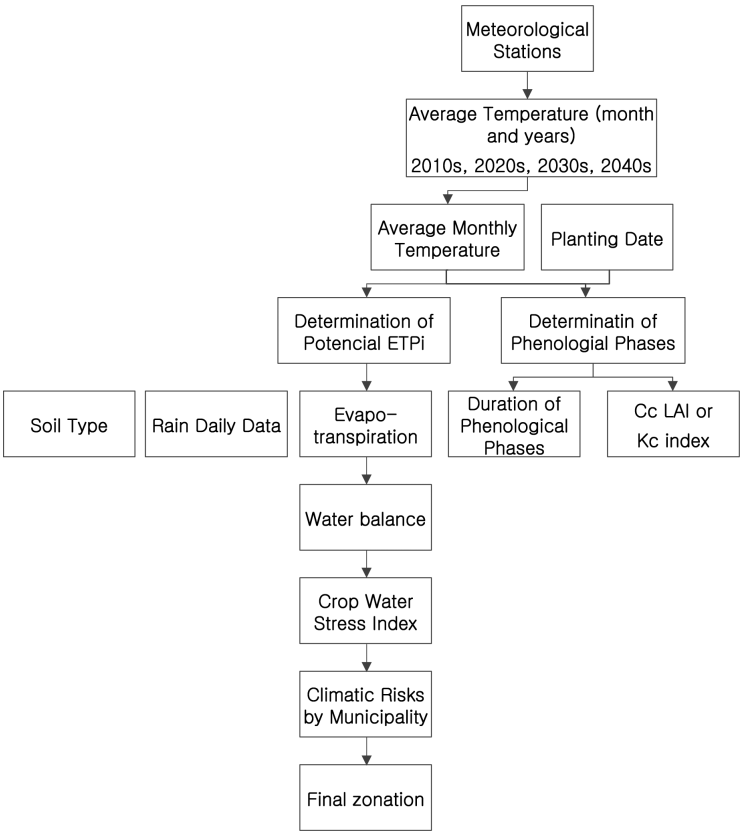


Fig. 3. Flowchart of the agricultural zonation of climatic risks for grains (Zullo Jr *et al.,* 2008).

the risk of frost or of high temperature is considered. It is important to note that this concept of fitness allows the simulation of an important agroclimate index that can be represented by altimetry as an easy way to map temperature. Regression equations developed for each region allow the estimation of maximum and minimum temperature as a function of latitude, longitude, and altitude. The altimetry data are obtained from USGS (United States Geological Survey), with contour lines established every 900 m horizontal distance, or 30 x 30 m in some cases.

Data and climate models

The annual water deficit is obtained from the simulation of the climatic water balance, where the monthly average temperature data are estimated from regional regression equations of temperature. The values of average monthly precipitation are calculated from the time-series of rainfall data available in the Agritempo system (www.agritempo.gov.br).

The availability of climate models, either global or regional, enabled the development of future scenarios, with lower or higher resolution for climatic variables including temperature, rainfall, and solar radiation.

In 2001, EMBRAPA and UNICAMP developed a method using global climate models with simulation of temperature increase according to global projection from IPCC (2001). This temperature was 1.2°C to 5.8°C (Pinto *et al.*, 2011). Recently published studies for Brazil (Assad and Pinto, 2008; Margulis *et al.*, 2011) used an agronomic model approach that evaluated how current climatic risks may be altered in the coming years based on projected temperature increases in IPCC scenarios. The key elements of the study were:

- Climate projections were derived via a regional circulation model (RCM) developed by UK's Hadley Center, called PRECIS (Providing Regional Climates for Impact Studies) that projects climate to the end of the century at 50 km × 50 km resolution (relevant to most municipality sizes).
- Nine major crops (cotton, rice, coffee, sugarcane, beans, sunflower, cassava, maize, and soybean), as well as pastures and beef cattle, altogether representing 86% of the planted area in Brazil, were assessed in terms of climate risks.
- Based on a 2007 baseline risk zone mapping in 5564 municipalities for these crops, the agricultural scenarios in Brazil were simulated for the 2010s (closest representation to the current conditions), 2020s, 2050s, and 2070s using two IPCC Scenarios: A2 (most pessimistic) and B2 (slightly more optimistic). In Scenario A2, the estimated global temperature rise is between 2°C and 5.4°C; and in B2, between 1.4°C and 3.8°C.

Future evapotranspiration indexes are calculated from the three RCMs (BRAMS, ETA, and PRECIS) and four GCMs (Moss *et al.,* 2010) by using IPCC SRES A2 scenarios based on climate (temperature) projection congruence for different regions of Brazil for the 2010s, 2020s, and 2030s. The selected GCMs included: NCCCSM (CCSM3) National Center for Atmospheric Research, USA; GIER (GISS-ER), NASA Goddard Institute for Space Studies, USA; CSMK3 (CSIRO Mk 3.0), Commonwealth Scientific and Industrial Research Organisation, Australia; and INCM3 (INM-CM3.0), Institute for Numerical Mathematics, Russia.

Results

The study revealed a significant reduction in Brazil's overall suitable area for cultivation of seven of the listed crops; sugarcane and cassava were not so severely affected (see Table 1).

The economic effects for each of the crops were calculated based on projected declines in crop area for the IPCC AR4 Scenarios A2 and B2. As the production of

Table 1. Impact of climate change on current "low risk" areas suitable for cultivation (Assad and Pinto, 2008; Margulis *et al.*, 2011).

	Variation relative to current productive area (%)					
	B2 Scenario			A2 Scenario		
Crops	2020	2050	2070	2020	2050	2070
Cotton	11	−14	−16	−11	−14	−16
Rice	−9	−13	−14	−10	−12	−14
Coffee	−7	−18	−28	−10	−17	−33
Sugarcane	171	147	143	160	139	118
Beans	−4	−10	−13	−4	−10	−13
Sunflower	−14	−17	−18	−14	−16	−18
Cassava	−3	−7	−17	−3	−13	−21
Maize	−12	−15	−17	−12	−15	−17
Soybean	−22	−30	−35	−24	−34	−41

a given crop is directly proportional to the cultivated area, the impact on the area is considered to have a direct impact on production and consequently on its value.

- The results reveal that, with the exception of sugarcane, the other eight major crops analyzed in these studies are projected to decrease production, which may be more severe in some regions, such as the northeast.
- Projected losses caused by climate change on all currently produced grains are close to US$4 billion by 2050, with the soybean sector alone accounting for almost 50% of the losses (Table 2).
- Under the pessimistic climate change scenario (A2), the best current coffee production ("low risk") areas are expected to decline by at least 30%, which could result in losses of ∼US$1 billion by 2050.
- However, even under the A2 Scenario, the area suitable for sugarcane could double by 2020.

The large range and magnitude of estimated production and economic impacts (up to ∼US$4 billion between 2020–2050) suggests an urgent need to improve the robustness of these estimates for:

- Planning and policy purposes to ensure robust agricultural and development targets by 2050 and beyond.
- Prioritizing climate adaptation and mitigation issues both in the national interest and in the post-Kyoto (2012) context.

The lack of data or access to long-term data that is currently not in digital form is a major constraint to (1) developing robust and accurate modeling projections and (2) calibrating and validating next-generation models. Despite the fact that the

Table 2. Percentage change in "low risk" cultivation areas in Brazil due to climate change under IPCC A2 Scenario and estimated economic loss.

Crops	Reduction of "low-risk" cultivation area (%)	Scenario A2 annual economic loss (million R$)*
Rice	−12	530
Cotton	−14	408
Coffee	−175	1, 597
Beans	−10	363
Soybean	−32	6, 308
Maize	−15	1, 511
Sugar cane	+145	0, 0
Total		10, 717

*(1 US$ = 2.2 Br$)

team had access to new data sources delivered by state institutions and the National Meteorological Institute, the quality of data did not allow for more accurate climate analyses compared to previous studies.

Global and regional climate models

Atmospheric general circulation models (AGCMs) are useful tools for representing the evolution of atmospheric processes at different time scales, ranging from weather to climate. Due to the large domain covered, the typical spatial resolutions of AGCMs are of the order of a few hundred kilometers. Therefore, AGCMs are not able to handle the large number of feedback processes occurring on subgrid scales controlled by local features such as topography, shorelines, vegetation, and lakes. These small-scale processes, as well as subgrid turbulent heat and momentum fluxes, cannot be described in detail by AGCMs. The use of regional climate models makes it possible to deal with those scales. Such models can be used for climate simulations on decadal time scales and are able to take into account subgrid scale climate feedback mechanisms. Outside the domain of the regional model, surface conditions such as sea surface temperature (SST), ocean ice, and three-dimensional atmospheric fields are generally provided by the global model. During the last decade, regional climate models with horizontal resolutions on the order of 10–20 km have become available.

The use of atmospheric or coupled atmospheric-ocean global models to investigate current and future climate has increased in the last years. However, the results obtained from those models lack regional detail due to coarse resolution. For example, at the regional scale precipitation and air temperature are influenced by topography, different land-use types, or proximity to the sea. This problem can be addressed through dynamical downscaling by using regional climate models.

The IPCC A2 scenario was chosen for the project because it describes more heterogeneity in the future with continued population growth and until 2040s the projections between Scenario A2 and B2 are very similar. Economic development is primarily region-specific, *per capita* economic growth and technological development are more fragmented and slower when compared with other scenarios (IPCC, 2007). The values of the upper limits (pessimistic) and lower limits (optimistic) temperature were selected.

Based on these methods, we found the following results for some important crops in Brazil (see Figs. 4 to 6): In all cases, there is little difference between the optimistic and pessimistic scenario in 2030. However, for all cases there is an increased risk area, where the risk of producing rice, beans, and cotton is higher than 70% in comparison with the current values of less than 20%.

Simulations Based on Process-Based Models

To examine the full range of climate change impacts on agriculture, process-based dynamic crop growth models are useful tools for assessing the biophysical effects of climate on crop growth and yield (e.g., Brisson *et al*., 2003; Jones *et al*., 2003; Keating *et al*., 1999; Palosuo *et al.,* 2011). These models have been accepted as predictors of the future impacts of climate change because their algorithms rely on

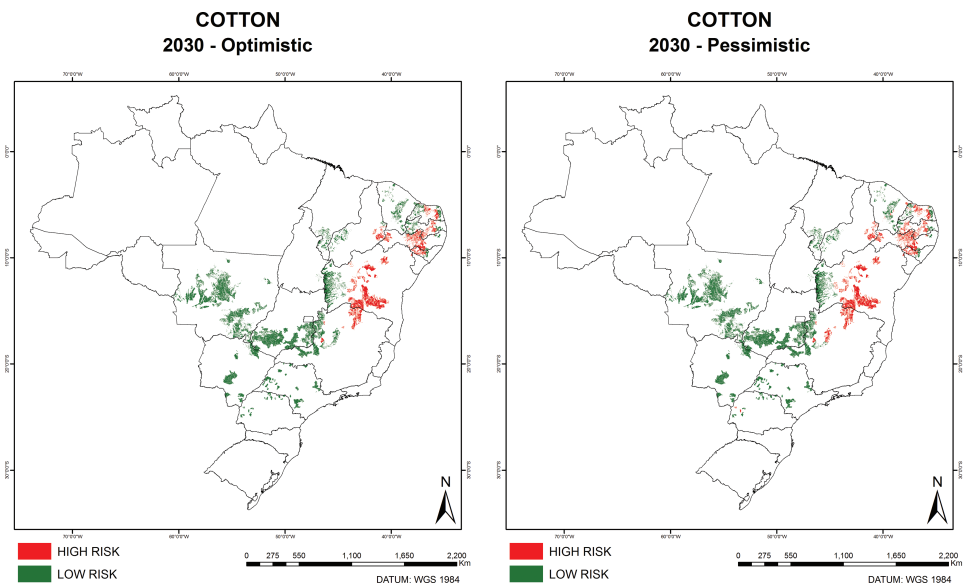


Fig. 4. Future projections for cotton simulated for two economic scenarios (Assad *et al.*, 2013, World Bank Report P118037).

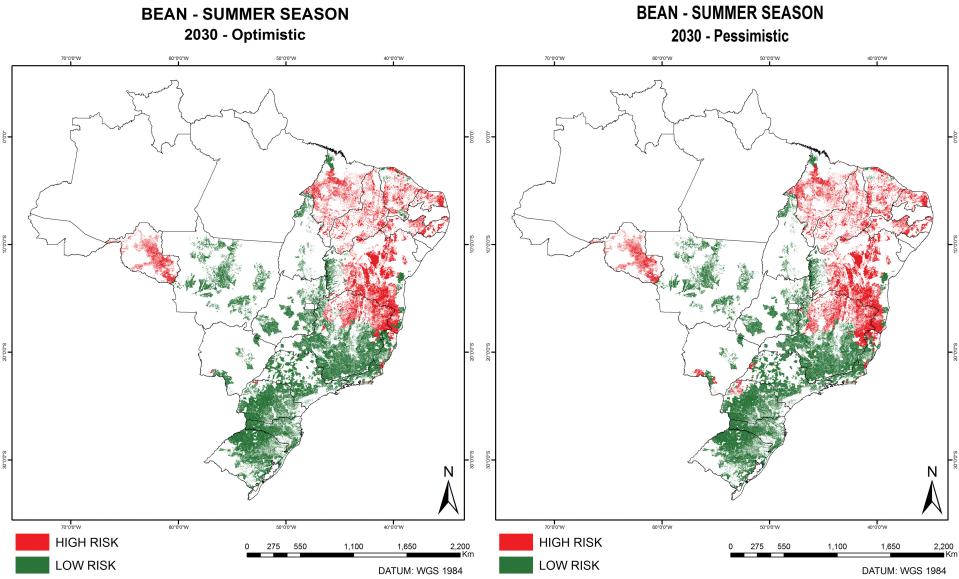


Fig. 5. Future projections for common bean crop simulated for two economic scenarios (Assad *et al.*, 2013, World Bank Report P118037).

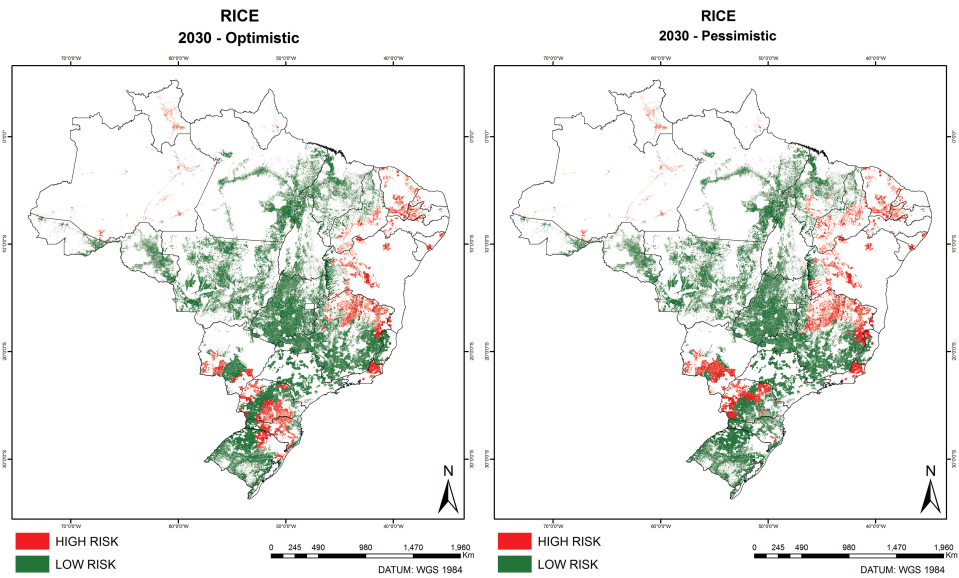


Fig. 6. Future projections for rice simulated for two economic scenarios (Assad *et al.*, 2013, World Bank Report P118037).

Table 3. Percentage change in areas at low risk from climate change.

	2020		2030	
Crops	Optimistic (%)	Pessimistic (%)	Optimistic (%)	Pessimistic (%)
Cotton	−4.6	−4.8	−4.6	−4.9
Rice	−10	−7, 4	−9, 1	−9.9
Sugarcane	107	101	108	91
Soybean	−13	−24	−15	−28
Rain-fed wheat	−41	−15.3	−31, 2	−20
Bean (summer season)	−54.2	−55.5	−54.5	−57.1
Bean (autumn season)	−63.7	−68.4	−65.8	−69.7
Maize (summer season)	−12	−19	−13	−22
Maize (autumn season)	−6, 1	−13	−7, 2	−15.3

state-of-the-art physiological and physical principles for a given species (Rosenzweig *et al.*, 2013). In this section, we explore the use of process-based models for evaluating climate change impacts on agriculture, by using sugarcane as a case study. In Brazil, there are few groups able to simulate crop growth on a country scale; sugarcane is one of the crops for which this skill is already developed. This crop is chosen because it is important for mitigating climate change, given that ethanol and biomass for energy are produced from it (Goldemberg, 2007). In addition nearly 75% of the world's sugar production comes from sugarcane and Brazil is the world's biggest sugarcane producer.

To simulate sugarcane growth under several future climate scenarios, we used the DSSAT/CANEGRO model (Inman-Bamber, 1991; Singels *et al.,* 2008), as it was shown to predict successfully Brazilian sugarcane in southern Brazil (Marin *et al.,* 2011). It simulates sugarcane growth in response to climate and to water inputs, based on a physiological description of sugarcane growth and development processes. By using a daily time-step, DSSAT/CANEGRO simulates leaf and tiller phenology; leaf area and canopy cover; leaf, stalk, and root biomass; and stalk sucrose mass. As inputs, the model requires soil parameters that regulate the soil water balance (e.g., drained upper and lower limit of plant available water, saturated water content, and maximum effective rooting depth), daily weather data (e.g., solar radiation; maximum and minimum air temperature; and precipitation), and irrigation timing and amounts. Crop simulations were based on the cultivar RB86-7515, which was used in 28% of the sugarcane production area in Brazil in 2010 (PMGCA, 2011), and cultivar calibration was done by using field data obtained in five locations in Brazil, which represent three distinct soils and climates, and a total of eight treatments (Marin *et al.,* 2012).

The current climate dataset (baseline) contains 79 weather stations distributed over the state of São Paulo and portions of the neighboring states of Parana, Mato Grosso do Sul, and Minas Gerais. These locations were identified as having at least eight years of continuous daily weather measurements within the 15-year period (1992–2007). One of the future climate simulations utilized here was performed with the HadRM3P Regional Climate Model from the UK Met Office (PRECIS for present-day (1961–1990) and future (2010–2100) conditions (Alves and Marengo, 2010; Marengo *et al*., 2009). To increase the range of future projections, this study also applied additional daily outputs of another global circulation model, namely CSIRO (Gordon *et al.,* 2002), for both A2 and B2 scenarios of climate change. Because the IPCC models investigated here vary in horizontal resolution (from 1.8 to 2.8°), the results presented have been interpolated to a 0.5×0.5 degree grid by applying OACRES (objective analysis using the Cressman scheme; Cressman, 1959).

None of the climate projections analyzed represented a yield loss for sugarcane in south Brazil, with gains ranging from 1% for PRECIS B2-late cycle to 54% for PRECIS A2-early cycle (Table 4). The largest gains were projected for the early cycle, followed by the medium and late cycle for all climate projections. This conforms to expectations, since areas harvested early normally produce larger

Table 4. Mean and standard deviation for stalk fresh mass (t/ha) and water-use efficiency (WUE, kg/[stalk DM] m^3 [ET]) for each climate scenario and percentage change compared to the baseline.

Harvest time	Model	Scenario	WUE (kg/m^3)		Stalk fresh mass (t/ha)	
Early	Baseline		4.20 ± 0.90	0%	73.1 ± 32.6	0%
	CSIRO	A2	6.01 ± 0.75	43%	91.7 ± 30.1	26%
		B2	4.84 ± 0.87	15%	79.3 ± 32.3	8%
	PRECIS	A2	6.64 ± 0.50	58%	$112. \pm 21.6$	54%
		B2	5.52 ± 0.69	32%	91.2 ± 24.2	25%
Medium	Baseline		3.98 ± 0.71	0%	66.8 ± 24.4	0%
	CSIRO	A2	5.68 ± 0.57	43%	82.4 ± 22.7	23%
		B2	4.57 ± 0.68	15%	71.8 ± 24.2	7%
	PRECIS	A2	6.31 ± 0.51	58%	99.5 ± 19.8	49%
		B2	5.24 ± 0.62	32%	81.5 ± 22.1	22%
Late	Baseline		4.40 ± 0.64	0%	70.3 ± 20.5	0%
	CSIRO	A2	6.12 ± 0.55	39%	84.7 ± 17.4	20%
		B2	5.01 ± 0.60	14%	75.4 ± 20.2	7%
	PRECIS	A2	6.23 ± 0.59	41%	86.9 ± 17.9	24%
		B2	5.10 ± 0.66	16%	71.2 ± 18.8	1%
Weighted average				34%		22%

amounts than areas harvested later. For the most commonly used cultivar in south Brazil, sucrose concentration follows a distinct trend, as medium cycle crops show higher sucrose concentration than early and late cycles. Therefore, we would expect increases in sucrose production mainly for the medium cycles given the rise in the stalk yield and the maintenance of high sucrose concentration in such fields. Knox *et al.* (2010) simulated climate change impacts for irrigated sugarcane production in Swaziland, and found similar trends for sucrose content and stalk fresh mass (SFM) for PRECIS downscaled projections for the 2050s, with a decreasing trend for future projections for both sucrose production and SFM, unless irrigation were included in the simulations.

Weighted averages for simulated (SFM) were 22% higher than the baseline (Table 4). Simulations using CSIRO climate projections resulted in an average increase of 15% compared to the baseline, while PRECIS climate projections resulted in a 29% increase. Interestingly, CSIRO projected rainfall increase by about 62% to 79%, mainly during the dry period of the year, with very small changes in temperatures for the A2 and B2 scenarios. PRECIS, on the other hand, projected an increase in temperature around 2°C for both economic scenarios, and decrease in rainfall by 25% to 30%. CSIRO projections also include a slight decrease in solar radiation while PRECIS scenarios had increased solar radiation, on average. These climate projection differences are distinctly reflected in sugarcane yields, because the routes to the outcomes were different for each of the climate projections used. For the CSIRO model, the yield increases occurred mostly because of projected higher rainfall. The PRECIS model, in turn, produced higher yields because of the positive effects of higher temperature during periods with adequate soil water supply, in addition to the elevated CO_2 concentrations.

Given the range of the results analyzed here, we can conclude that the benefit of increased temperature and elevated CO_2 concentration may override the disadvantage of reduced rainfall (as projected by PRECIS) for sugarcane crops in south Brazil. However, sugarcane may also be limited by solar radiation, not only by rainfall (Vu and Allen, 2009).

Besides the increase in average yield, future climate projections also present a decrease in the SFM temporal variability for the three harvest dates, which would correspond to a reduction in the production risks for sugarcane, mainly for the PRECIS projections in the early and medium cycles. The lower probability of low yields in future climates represents a major favorable impact for Brazil as a whole and needs to be further investigated. Recently, oscillations in sugarcane yields due to weather and management have had social and economic repercussions, with several sugar mills closing doors, which has resulted in thousands of unemployed workers.

Maps of SFM variation (Fig. 7) show the major SFM increases for the central-north region of the state of São Paulo, which has soils with high water-holding

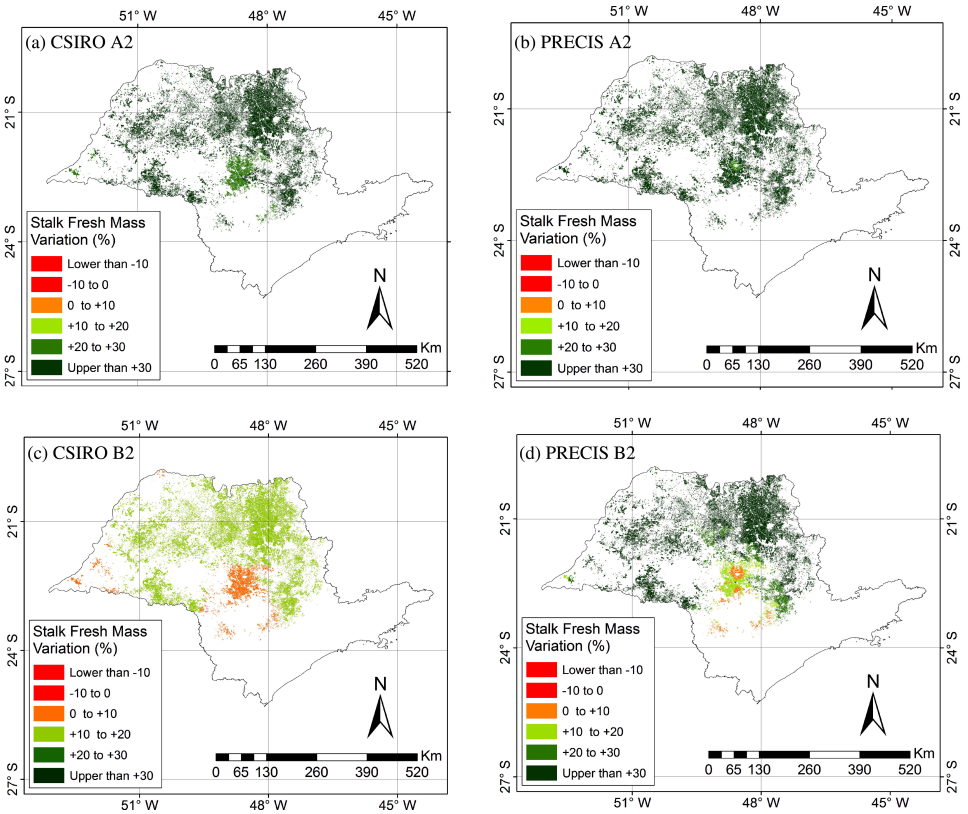


Fig. 7. Spatial distribution of the difference in SFM simulated for the baseline growing area of sugarcane within the state of São Paulo in 2011 and for future projections based on downscaled A2 and B2 scenarios from CSIRO and PRECIS.

capacity, adequate temperatures, and high amounts of rainfall and solar radiation. Results show that the area that is currently being used for sugarcane in São Paulo is projected to experience higher yield gains than those predicted to occur for the entire state of São Paulo. This may be related to climate conditions in the central and northern parts of the state where the climate is hotter and drier than the southern part, where sugarcane has not been cultivated (Fig. 7). Under an increased temperature scenario, south São Paulo state may become more suitable for sugarcane production in the future, since currently the cold period limits sugarcane growth and yield. On the other hand, it is reasonable to argue that the western and northwestern part of the state would be favorably affected by climate change (Fig. 7), due to current water and temperature stresses on sugarcane, which should enhance the effect of CO_2 fertilization on photosynthesis and yield (Marin *et al*., 2011).

AgMIP South America

With the current strengthening of policy research on climate change and agriculture in Brazil, EMBRAPA is partnering with AgMIP for the AgMIP South America project. The project was established to use advanced approaches for assessing impacts of climate change and variability on agriculture in Brazil and to evaluate adaptation options that will lead to more resilient agricultural systems, increased food security, and reduced poverty in Brazil. Through this partnership, AgMIP and EMBRAPA will cooperate in research for advancing agricultural models and scientific capabilities for integrated assessments of climate change impacts and adaptation, as well as collaborate in activities that lead to improved agricultural models, data, methods, and assessments.

Conclusion

The framework of the AgMIP protocols complements the modeling of crops in Brazil. The evolution of this research base now allows the possibility to compare at least three crop models; DSSAT, APSIM, and STICS (Simulateur multidisciplinaire pour les cultures standards, Brisson *et al*., 2003). The Brazilian researchers participating in AgMIP created the AgMIP-BR project to provide advances in comparing model results in locations across the world. Since 2014, the Brazil AgMIP team has participated in the development of the AgMIP ATLAS Project (Agro-Economic Dynamics and Trade-offs of Land Use and **S**ustainability). The AgMIP ATLAS project will undertake the research needed to understand the system dynamics, map emerging hot-spots of food-security and environmental degradation, identify global-change test-beds for targeted interventions, and conduct improved scenario-based multi-model assessments of adaptation strategies and tradeoffs on the global scale and in specific focal regions. The resulting atlas of consistent multi-scale information products will guide decision-makers in a challenging and interconnected future.

Another important result is the cooperation agreement between EMBRAPA and the USDA for effective collaboration in the AgMIP program.

The possibility of using the AgMIP protocols for regional integrated assessments is already helping to identify areas of high climatic risk in Brazil for the next 20 years and to estimate the productivity of the main Brazilian crops. Advanced studies of extreme events show the need for Brazil to quickly search for adaptation options for agriculture, which plays a significant role in the national economy. Taken together, these activities have great potential to contribute to science-based public policies linked to climate change in the country.

References

Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Klein Tank, A., Haylock, M., Collins, D., Trewin, B., Rahimzadeh, F., Tagipour, A., Ambenje, P., Rupa Kumar, K., Revadekar, J., Griffiths, G., Vincent, L., Stephenson, D., Burn, J., Aguilar, E., Brunet, M., Taylor, M., New, M., Zhai, P., Rusticucci, M., and Vazquez-Aguirre, J. L. (2006). Global observed changes in daily climate extremes of temperature and precipitation, *J. Geophys. Res.*, **111**, D05109.

Alexandrov, V. A. and Hoogenboom, G. (2000). The impact of climate variability and change on crop yield in Bulgaria *Agr. For. Met.*, **104**, 315–327.

Alves, L. and Marengo, J. (2010). Assessment of regional seasonal predictability using the PRECIS regional climate modeling system over South America, *Theor. Appl. Clim.*, **100**(3), 337–350.

Assad, E. D., Buainain, A. M., Pinto, H. S., Sousa, M. R., and Duarte, V. (2013). "Climate Changes: Challengers for Brazil", in Dhirendra Vajpeyi, K. (Org.), *Climate Changes: Challengers for Brazil*, Lexington Books, Plymouth, pp. 169–200.

Assad, E. D., Martins, S. C., Beltrao, N. E., and Pinto, H. S. (2013). Impacts of climate change on the agricultural zoning of climate risk for cotton cultivation in Brazil, *Pesquisa Agropecuária Brasileira*, **48**, 1–8.

Assad, E., Pinto, H. S., Nassar, A., Harfuch, L., Freitas, S., Farinelli, B., Lundell, M., and Fernandes, E. C. M. (2012). *Impactos das Mudanças Climáticas na Produção Agrícola Brasileira, Report # P118037*, p. 89.

Assad, E., Pinto, H. S., Nassar, A., Harfuch, L., Freitas, S., Farinelli, B., Lundell, M., and Fernandes, E. C. M. (2013). *Impacts of Climate Change on Brazilian Agriculture. World Bank. Report P118037*, World Bank, Washington, DC, p. 88.

Brisson, N., Rugeta, F., Gateb, P., Lorgeouc, J., Nicoullauda, B., Tayotd, X., Pleneta, D., Jeuffroya, M. H., Bouthierb, A., Ripochea, D., Marya B., and Justesa, E. (2003). STICS: a generic model for simulating crops and their water and nitrogen balances. II. Model validation for wheat and maize, *Agronomie*, 22, 69–92.

Camargo, A. and Camargo, M. B. (1983). "Paes. Teste de uma equação simples para estimativa da evapotranspiração potencial baseada na radiação solar extraterrestre e na temperatura do ar", *Congresso Brasileiro De Agrometeorologia*, pp. 229–244.

Carvalho, J. R. P., Assad, E. D., Evangelista, S. R. M., and Pinto, H. S. (2013). Estimation of dry spells in three Brazilian regions-Analysis of extremes, *Atmos. Res. Print*, **132–133**, 12–21.

Cressman, G. P. (1959). An operational objective analysis system, *Mon. Weather Rev.*, **87**, 367–374.

Goldemberg, J. (2007). Ethanol for a Sustainable Energy Future, *Science*, **315**(5813), 808–810.

Gordon, H. B., Rotstayn, L. D., McGregor, J. L., Dix, M. R., Kowalczyk, E. A., O'Farrell, S. P., Waterman, L. J., Hirst, C. A., Wilson, S. G., Collier, M. A., Watterson, I. G., and Elliott, T. I. (2002). *The CSIRO Mk3 Climate System Model, Technical Report 60*, CSIRO Atmospheric Research, Aspendale.

Groissman, P., Knight, P., Easterling, D., Karl, T., Hegerl, G., and Razuvaek, V. (2005). Trends in intense precipitation in the climate record, *J. Clim.*, **18**, 1326–1350.

Inman-Bamber, N. G. (1991). A growth model for sugarcane based on a simple carbon balance and the CERES-Maize water balance, *S. Afr. J. Plant Soil*, **8**(2), 93–99.

Jones, J. W., Hoogenboom, G. Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J.T. (2003). The DSSAT cropping system model, *Europ. J. Agronomy* **18**, 235–265.

Keating, B. A., Robertson, M. J., Muchow, R. C., and Hut, N. I. (1999). Modelling sugarcane production systems I. Development and performance of the sugarcane module, *Field Crops Res.*, **61**, 253–271.

Knox, J. W., Rodríguez Díaz, J. A., Nixon, D. J., and Mkhwanazi, M. (2010). A preliminary assessment of climate change impacts on sugarcane in Swaziland, *Agric. Syst.*, **103**(2), 63–72.

MAPA (2014) Exportações do agronegócio atingem quase US$ 100 bilhões em 2013. Available at: http://www.agricultura.gov.br/comunicacao/noticias/2014/01/exportacoes-do-agronegocio-atingem-quase-uss-100-bilhoes-em-2013. Accessed on 21 March 2014.

Marengo, J. A., Jones, R., Alves, L. M., and Valverdem, M. C. (2009). Future change of temperature and precipitation extremes in South America as derived from the PRECIS regional climate modeling system, *Int. J. Clim.*, **29**(15), 2241–2255.

Margulis, S., Dubeux, S. B. C., and Marcovich, J. (2011). The Economy of Climate Change in Brazil, Synergia, Rio de Janeiro, p. 331.

Marin, F. R., Jones, J. W., Royce, F., Suguitani, C., Donzelli, J. L., Pallone, W. J. F., and Nassif, D. S. P. (2011). Parameterization and Evaluation of Predictions of DSSAT/CANEGRO for Brazilian Sugarcane, *Agron. J.*, **103**(2), 304–314.

Marin, F. R., Jones, J. W., Singels, A., Royce, F., Assad, E. D., Pellegrino, G. Q., and Justino, F. (2012). Climate change impacts on sugarcane attainable yield in Southern Brazil, *Clim. Change*, **117**, 227–239.

Margulis, S. Dubeux, C. B. S., and Marcovitch, J. (2010). *Economia da Mudança do Clima no Brasil: Custos e Oportunidades* IBEP Gráfica, São Paulo.

Metz, B. Davidson, O. R., Bosch, P. R., Dave, R., and Meyer, L. A. (eds.) (2007). *IPCC — 2007 Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007* Cambridge University Press, Cambridge.

Monteiro, J. E. B. A., Azevedo, L. C., Assad, E. D., and Sentelhas, P. C. (2013). Rice yield estimation based on weather conditions and on technological level of production systems in Brazil, *Pesquisa Agropecuária Brasileira*, **48**, 123–131.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks. T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

OECD/FAO (2012). *Agricultural Outlook 2012*. Available at: http://www.oecd-ilibrary.org/agriculture-and-food/oecd-fao-agricultural-outlook- 2012_agr_outlook-2012-en. Accessed on 21 March 2014.

Palosuo, T., Kersebaumb, K. C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., Patil, R. H., Ruget, F., Rumbaur, C., Takac, J., Trnka, M., Bindi, M., Çaldag, B., Ewert, F., Ferrise, R., Mirschel, W., Saylan, L., Siska, B., and Rötter, R. (2011). Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models, *Eur. J. Agron.*, **35**, 103–114.

Pinto, H. S. and Assad, E. D. (2008). Global Warming and the new geography of agricultural production in Brazil. Available at: http://www.cpa.unicamp.br/aquecimento_agricola_en.html. Accessed on 21 March 2014.

Pinto, H. S., Assad, E. D. and Pellegrino, G. Q. (2011). "Adaptação à Mudança do Clima — Setor Agrícola", in Margulis, S., Dubeux, C., and Marcovitch, J. (Orgs.), *Economia da Mudança do Clima no Brasil*, Synergia Editora, Rio de Janiero, **1** 165–175.

PMGCA (2011). *Cultivar census for 2010/2011 sugarcane growing season*. Available at: http://pmgca.dbv.cca.ufscar.br/htm/catal/censovar.php. Accessed on 21 March 2014.

Rosenzweig, C., Jones, J. W., Hatfield, J. L, Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C, Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., and Winter, J. M. (2013). Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–182.

Singels, A., Jones, M., van den Berg, M. (2008). *DSSAT v4.5 Canegro Sugarcane Plant Module: Scientific documentation*, SASRI, Mount Edgecombe, South Africa, p. 34.

Vu, J. C. V. and Allen Jr., L. H. (2009). Stem juice production of the C4 sugarcane (Saccharum officinarum) is enhanced by growth at double-ambient CO_2 and high temperature, *J. Plant Physiol.*, **166**(11), 1141–1151.

Zullo Jr. J., Pinto, H. S., and Assad, E. D. (2006). Impact assessement study of climate change on agricultural zoning, *Meteorol. Appl.*, **1**, 69080.

Zullo Jr. J., Pinto, H. S., Assad, E. D., and Evangelista, S. R. (2008). *Potential Economic Impacts of Global Warming on Two Brazilian Commodities, According to IPCC Prognostics*, Terrae, Campinas.

Chapter 12

AgMIP Regional Activities in a Global Framework: The China Experience

Fulu Tao[1] and Erda Lin[2]

[1]*Chinese Academy of Sciences, Beijing, China*

[2]*Chinese Academy of Agricultural Sciences, Beijing, China*

Introduction

China's arable land (Fig. 1), which represents less than 10% of the total arable land in the world, supports over 20% of the world's population. Of this approximately 1.4 million square kilometers of arable land, only about 1.2% (116,580 square kilometers), permanently supports crops and 525,800 square kilometers are irrigated. About 75% of China's cultivated area is used for food crops. Rice is China's most important crop, and is raised on about 25% of the cultivated area. During the last three decades, rice production represented 41% to 45% of total grain production in the country. Since 1970, China has accounted for nearly one fourth of the total rice-sown area and more than one third of total rice production in the world (State Environmental Protection Administration, 2003). The majority of rice is grown in south China in the middle and lower reaches of the Yangtze River, as well as in northeast China (Fig. 1). Wheat is the second most prevalent grain crop, and is grown in most parts of the country, but especially on the Huang-Huai-Hai Plain, and the Wei and Fen River valleys on the Loess Plateau. Since 1980s, China has continued to hold the greatest share of world wheat production, averaging 112 M t from 2006 to 2010 (FAO, 2012). China also produces more than 20% of total maize production annually in the world. Maize and soybean are mainly grown in north and northeast China.

During the past few decades, China has experienced a strong warming trend. The average annual temperature across the country has increased by 1.2°C since 1960. Cold extremes have decreased while warm extremes have increased over the

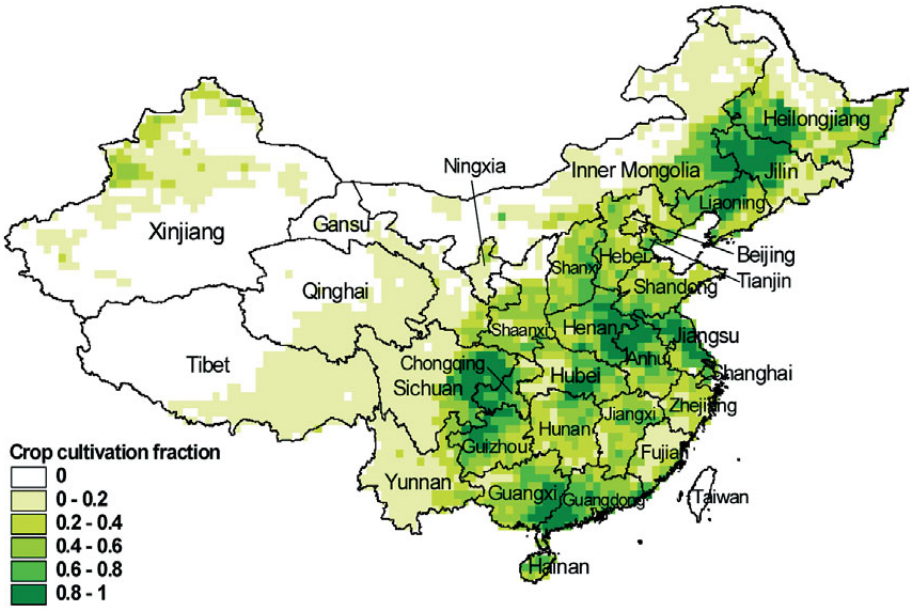


Fig. 1. Crop cultivation fractions around 2000 and provinces (autonomous region or municipality) in China.

past 50 years (Zhai and Pan, 2003). The number of frost days in China has reduced significantly.

From 1960 to 2006, although there is no significant trend in mean annual precipitation for China as whole, there are distinct regional and seasonal differences. The drier regions of north China and northeast China are receiving less precipitation in the summer and autumn months. By contrast, the wetter region of south China is experiencing more rainfall during both summer and winter (Piao *et al.*, 2010). Significant increases in extreme precipitation have been found in west China, the mid-lower reaches of the Yangtze River, and parts of the southwest and south of China coastal area (Piao *et al.*, 2010; Zhai *et al.*, 2005).

Climate Impacts on Agricultural Production in China Since 1980

The changes in the frequency and characteristics of weather and climate extremes have had a major impact on agricultural production. Climate trends in 1980–2008 have had measureable impacts on crop yields, although with large spatial differences. The particular crops and regions that have been most affected and should be priorities for adaptation are maize and wheat in the arid and semi-arid areas of north and

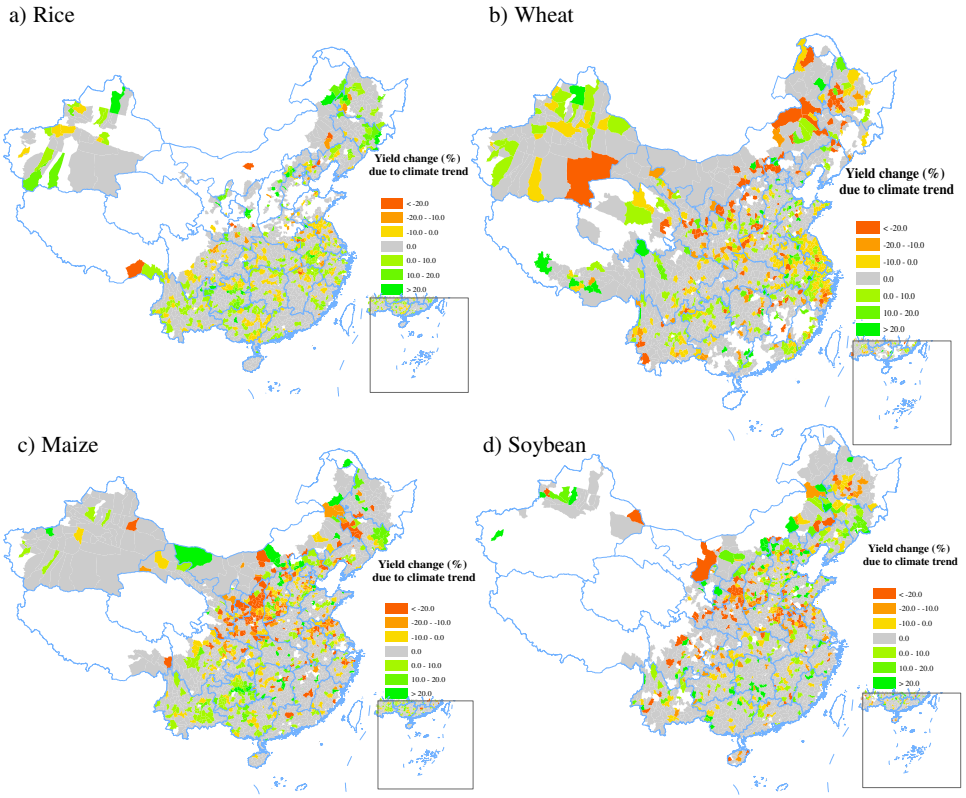


Fig. 2. Crop yield change due to climate trends during 1980–2008, for (a) rice, (b) wheat, (c) maize, and (d) soybean. Maps are for the purpose of geographic information reference only.

northeast China, where droughts induced by climate warming and increasing solar radiation could limit the benefits of improved thermal conditions (Fig. 2).

Based on crop planting area and total production by county in 2008, planting area-weighted averages across China showed that climate trends overall reduced wheat, maize, and soybean yields by 1.27%, 1.73%, and 0.41%, respectively; in contrast, rice yield increased by 0.56% (Tao *et al.*, 2012). The seemingly small impact on average crop yields resulted in a major impact on total production. Climate trends as a whole reduced wheat and maize production by 3.60×10^5 t and 1.53×10^6 t, respectively; conversely, rice and soybean production increased by 7.44×10^4 t and 4.16×10^3 t, respectively. For soybean, there were relatively large low-yielding areas with yield negatively affected, as well as relatively small high-yielding areas with yield positively affected. As a result, the soybean planting area weighted average of yield change was negative, but the total production change was positive.

Evaluating Future Climate Impacts on Agricultural Production in China

Methods of study

A probabilistic assessment approach to project crop productivity and water use change against a global mean temperature (GMT) increase scale when using process-based crop models and multiple climate scenarios

For each representative station, we first used historical daily weather data from 1961 to 1990 to parameterize a weather generator and to generate 100 years of daily weather data, which represented the baseline climate conditions. Then we identified the projected climate changes and atmospheric CO_2 concentrations at the station on the basis of global climate models (GCMs) and Special Reports on Emissions Scenarios (SRES) and their projected time-series of annual GMT change (IPCC, 2001b). Next, we identified the median values in the projected changes in monthly mean of climate variables, minimum temperature (T_{min}), maximum temperature (T_{max}), precipitation, and solar radiation (*Srd*), then used them to alter the parameters in the weather generator, to generate 100 years of daily weather data for GMT changes of 1, 2, and 3°C, respectively. Finally, we ran the validated CERES crop model (Jones *et al.*, 2003) by using both the baseline climate conditions and the climate change scenarios for GMT changes of 1, 2, and 3°C for 100 years, respectively. We calculated the changes in growing period, maize yield, evapotranspiration (ET), and irrigation water use between the future climate change scenarios and the baseline climate conditions and further investigated the probability distribution of the resultant changes for GMT changes of 1, 2, and 3°C, respectively.

A new super-ensemble-based probabilistic projection system to assess the impacts of climate change and climate extremes on crop productivity and water use

A new super-ensemble-based probabilistic projection system (SuperEPPS) was developed to assess the effects of climate change and variability on regional crop productivity and water use in a probabilistic framework, to account for the uncertainties that arise from CO_2 emission scenarios and climate change scenarios, as well as from biophysical processes (Tao *et al.* 2009a, 2009b; Tao and Zhang, 2010). In the study, by using multiple optimal sets of parameters, the model to capture the crop–weather relationship over a large area (MCWLA) family of crop models (Tao *et al.* 2009a, 2009b) was driven by baseline climate conditions (1961–1990) and ten future climate scenarios each for the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100), which resulted in a super-ensemble-based projection. The

mean CO_2 concentration during 1961–1990 was set at 330 ppmv. The mean CO_2 concentrations were set at 436.0 (424.5) ppmv for the 2020s, 602.5 (498.5) ppmv for the 2050s, and 842.0 (541.0) ppmv for the 2080s, under the A1FI (B1) scenario (IPCC, 2001). Finally, for each $0.5^\circ \times 0.5^\circ$ crop cultivation cell in major crop production provinces, we calculated the changes in rice productivity and ET by using each set of simulation results during the 2020s, 2050s, and 2080s relative to the corresponding simulation for 1961–1990.

Crop model results

Probabilistic change of crop productivity and water use with GMT increase of 1, 2, and 3°C with CERES crop models

After assessing six representative stations across China, we projected probabilistic changes in rice yield, growing period, ET, and irrigation water use for GMT changes of 1, 2, and 3°C. Without consideration of CO_2 fertilization effects, our results indicate that the growing period would shorten with 100% probability; yield would decrease with a probability of 90%, 100%, and 100% for GMT changes of 1, 2, and 3°C, respectively. The median values of yield decrease ranged from 6.1% to 18.6%, 13.5% to 31.9%, and 23.6% to 40.2% for GMT changes of 1, 2, and 3°C, respectively. According to the median values of the projected changes, ET and irrigation water use would decrease in most of the investigated stations. If CO_2 fertilization effects were included, the rice-growing period would also be reduced with 100% probability; across the stations the median values of yield changes ranged from −10.1% to 3.3%, −16.1% to 2.5%, and −19.3% to 0.18% for GMT changes of 1, 2, and 3°C, respectively. ET and irrigation water use would decrease more and with higher probability in comparison with the simulations without consideration of CO_2 fertilization effects. Our study presents a process-based probabilistic assessment of rice production and water use at different GMT increases, which is important for identifying which climate change level is dangerous for food security.

For wheat, results show that, because of temperature increase, projected wheat-growing periods for GMT changes of 1, 2, and 3°C would shorten, with averaged median values of 3.94%, 6.90%, and 9.67%, respectively (Liu and Tao, 2013). There is a high probability of decreasing changes in yield and water-use efficiency under higher temperature scenarios *without* consideration of CO_2 fertilization effects, but changes in yield and water-use efficiency under higher temperature scenarios *with* consideration of CO_2 fertilization effects show a high probability of increasing. Elevated CO_2 concentrations generally compensate for the negative effects of warming temperatures on production. Moreover, positive effects of elevated CO_2 concentration on grain yield increase with warming temperatures.

For maize, our results indicate that median values of projected decreases in the yields of irrigated maize without (with) consideration of CO_2 fertilization effects ranged from 1.4% to 10.9% (1.6% to 7.8%), 9.8% to 21.7% (10.2% to 16.4%), and 4.3% to 32.1% (3.9% to 26.6%) for GMT changes of 1, 2, and 3°C, respectively. Median values of projected changes in irrigation water use without (with) consideration of CO_2 fertilization effects ranged from –1.3% to 2.5% (–18.8% to 0.0%), –43.6% to 2.4% (–56.1% to –18.9%), and –19.6% to 2.2% (–50.6% to –34.3%), which were ascribed to rising CO_2 concentration and increased precipitation, as well as reduced growing period. For rainfed maize, median values of projected changes in yields without (with) consideration of CO_2-fertilization effects ranged from –22.2% to –1.0% (–10.8% to 0.7%), –27.6% to –7.9% (–18.1% to –5.6%), and –33.7% to –4.6% (–25.9% to –1.6%).

Probabilistic change of crop productivity and water use during the 2020s, 2050s, and 2080s, with MCWLA crop models

Rice yields

For all rice cultivation cells across Anhui province, the histogram and cumulative density function (CDF) of rice yield changes from a large number of super-ensemble simulations (44 grids × 30 sets of parameters × 30 years × 10 scenarios = 396,000 simulations) showed that if CO_2 fertilization effects were taken into account, the probability of the rice yield increasing during the 2020s, 2050s, and 2080s relative to the 1961–1990 level was respectively 87.5%, 68.6%, and 60.0%. The simulated rice yield increased on average by 10.6%, 7.1%, and 0.7%, respectively. If CO_2 fertilization effects were not taken into account, the probability of the rice yield decreasing during the 2020s, 2050s, and 2080s relative to the 1961–1990 level was, respectively, 77.3%, 84.4%, and 90.0%, and the simulated rice yield decreased on average by 4.9%, 18.6%, and 29.4%, respectively, owing to climate change.

For all rice cultivation cells across Jiangsu province, the histogram and CDF of rice yield changes from a large number of super-ensemble simulations (37 grids × 30 sets of parameters × 30 years × 10 scenarios = 333,000 simulations) showed that if CO_2 fertilization effects were taken into account, the probability of the rice yield increasing during the 2020s, 2050s, and 2080s relative to the 1961–1990 level was, respectively, 93.5%, 80.0%, and 71.2%. The simulated rice yield increased on average by 11.4%, 13.2%, and 7.8%, respectively. If CO_2 fertilization effects were not taken into account, the probability of the rice yield decreasing during the 2020s, 2050s, and 2080s relative to the 1961–1990 level was, respectively, 73.0%, 78.5%, and 87.1%, and the simulated rice yield decreased on average by 3.7%, 13.4%, and 23.8%, respectively.

For all rice cultivation cells across Zhejiang province, the histogram and CDF of rice yield changes from a large number of super-ensemble simulations (28 grids $\times$ 30 sets of parameters $\times$ 30 years $\times$ 10 scenarios = 252,000 simulations) showed that if CO_2 fertilization effects were taken into account, the probability of the rice yield increasing during the 2020s, 2050s, and 2080s relative to the 1961–1990 level was, respectively, 88.5%, 77.5%, and 66.7%. The simulated rice yield increased on average by 9.5%, 11.3%, and 4.0%, respectively. If CO_2 fertilization effects were not taken into account, the probability of the rice yield decreasing during the 2020s, 2050s, and 2080s relative to the 1961–1990 level was, respectively, 82.2%, 84.4%, and 92.1%, and the simulated rice yield decreased on average by 5.9%, 15.7%, and 27.1%, respectively. In addition, in all three provinces, the yield variability, as indicated by the standard deviation of the simulated yields during the 2020s, 2050s, and 2080s, increased with climate change. These rice yield results are compared to previous studies in Table 1.

Results showed that winter wheat yields in the North China Plain (NCP) could increase with high probability in the future due to climate change. During the 2020s, 2050s, and 2080s, with (without) CO_2 fertilization effects relative to the 1961–1990 level, simulated wheat yields would increase on average by up to 37.7% (18.6%), 67.8% (23.1%), and 87.2% (34.4%), respectively, across 80% of the study area. Simulated changes in ET during the wheat-growing period ranged generally from -6% to 6% (-0.6% to 10%), from -10% to 8% (-1.0% to 17%), and from -17% to 4% (7–12%), respectively, across the study area.

Further analyses suggested that improvements in heat and water resources and rising atmospheric CO_2 concentration ($[CO_2]$) could contribute notably to wheat productivity increase in the future. Climate change could enhance the development and photosynthesis rate; however the duration of the reproductive period could be less affected than that of vegetative period, and wheat productivity could benefit from enhanced photosynthesis due to climate change and rising $[CO_2]$. Furthermore, wheat could become mature earlier, which could lead to avoidance of severe high temperature stress. This study explicitly parameterized the effects of high temperature stress on productivity, accounted for a wide range of crop cultivars with contrasting phenological and thermal characteristics, and presents new findings on the probabilistic responses of wheat productivity and water use to climate change in the NCP.

Wheat yields

The estimates on wheat yields changes due to climate change in China display a wide range of values. By driving the CERES-wheat model on a regional scale with regional climate model (RCM) output, Lin *et al.* (2005) showed that under the IPCC SRES A2 with CO_2 fertilization effects irrigated wheat yields in China

Table 1. Summary of the effects of climate change on simulated rice yield in China.

Study region	Study period	Climate change scenario	Crop model	Projected yield changes with CO_2 fertilization effects	Projected yield changes without CO_2 fertilization effects	References
Four agroecological zones across China	[CO_2] doubled	GFDL GCM 2× [CO_2] GISS GCM 2× [CO_2] UKMO GCM 2× [CO_2]	ORYZA1	–7.4% to 5.8% –21.7% to 5.8% –27.6% to 3.1%		Matthews *et al.*, 1997
Four agroecological zones across China	[CO_2] doubled	GFDL GCM 2× [CO_2] GISS GCM 2× [CO_2] UKMO GCM 2× [CO_2]	SIMRIW	–10.0% to 9.7% –30.7% to 9.7% –17.2% to –1.4%		Matthews *et al.*, 1997
Selected stations in south China	2071–2090	PRECIS RCM B2 emission scenario	CERES-rice	5% to 20%	–7% to –0.25%	Yao *et al.*, 2007
Rice cultivation areas across China	2010–2019 2040–2049 2070–2079	PRECIS RCM A2 emission scenario	CERES-rice	15.1% 7.9% –0.8%	6.2% –7.7% –20.9%	Xiong *et al.*, 2008

Rice cultivation areas across China	2010–2019 2040–2049 2070–2079	PRECIS RCM B2 emission scenario	CERES-rice	2.2% –1.8%, –2.6%	–5.8% –13.7%, –19.1%	Xiong *et al.*, 2008
Six representative stations across China	GMT change of 1°C 2°C 3°C	Probabilistic climate scenarios generated by Monte Carlo technique	CERES-rice	–10.1% to 3.3% –16.1% to 2.5% –19.3% to 0.18%	–18.6% to –6.1% –31.9% to –13.5% –40.2% to –23.6%	Tao *et al.*, 2008
East China	2071–2100	RegCM3 RCM A2 emission scenario	EPIC	6.5%		Chavas *et al.*, 2009
Middle and lower reaches of Yangtze River	2021–2050	PRECIS RCM B2 emission scenario	ORYZA2000	$\leq -14\%$		Shen *et al.*, 2011
East China	2011–2040 2041–2070 2071–2100	Combinations of five GCMs (HadCM3, PCM, CGCM2, CSIRO2 and ECHAM4) and two emission scenarios (A1FI and B1)	MCWLA-rice	9.5% to 11.4% 7.1% to 13.2% 0.7% to 7.8%	–5.9% to –3.7% –18.6% to –13.4% –29.4% to –23.8%	Tao and Zhang, 2013

would increase on average, in comparison with the period 1961–1990, by 13.3% (with a range from –65% to 655%), 25.1% (with a range from –63% to 558%), and 40.3% with a range from (–53% to 458%), during the 2020s, 2050s and 2080s, respectively. Under the IPCC SRES B2, the corresponding values were 11.0% (with a range from −89% to 485%), 14.2% (with a range from −80% to 278%), and 25.5% (with a range from −70% to 378%) Recently updated estimates showed that under the IPCC SRES A2 (B2) with CO_2 fertilization effects, irrigated wheat yields in China would increase on average by 12.0% (2.7%), 20.3% (6.7%), and 26.7% (10.6%) compared to the simulated yields in 1961–1990 during the 2020s, 2050s, and 2080s, respectively. Without CO_2 fertilization effects, the corresponding values under the IPCC SRES A2 (B2) are 1.3% (−6.4%), −2.0% (−8.8%) and −8.8%, (−11.6%), respectively (Xiong *et al.*, 2008).

By driving the EPIC model with RCM output under the A2 emission scenario, Chavas *et al.* (2009) indicated that potential yield was projected to increase on average by 24.9% for rainfed winter wheat in eastern China during 2071–2100 with CO_2 fertilization effects, relative to 1961–1990, although with large spatial variability. In much of the NCP, simulated wheat yield could increase by 30–70%, and the largest increase could be up to 100–200%. Mo *et al.* (2009), by driving a vegetation process-based model with HadCM3 GCM output in the NCP, showed that irrigated winter wheat yield would increase by 19% under the A2 scenarios during the 2070s and by 13% under B1 scenarios during the 2060s. Guo *et al.* (2010) found that, by driving the CERES-wheat model with a climate scenario based on the HadCM3 GCM and the B2A scenario at seven sites in the NCP, irrigated wheat yields would increase on average by 9.8% in 2090s without CO_2 fertilization effects, and that wheat yields would increase by an additional 38% if CO_2 fertilization effects were included.

Maize yields

For maize, the resulting probability distributions indicate expected yield changes of –9.7, –15.7, and –24.7% across the maize cultivation grids in Henan province during the 2020s, 2050s, and 2080s, with 95% probability intervals of −29.4, +15.8; −45.7, +24.0; and −92.8, +20.3 (as a percentage of 1961–1990 yields), respectively. The corresponding values in the Shandong province were −9.1%, −19.0%, and −25.5%, with 95% probability intervals of (−28.4, +17.4), (−45.4, +15.9), and (−60.1, +12.8). We also investigated the temporal and spatial pattern of changes and variability in maize yield across the region. Besides the new findings on the probabilistic changes of maize productivity in the NCP, our study demonstrated an advanced super-ensemble-based probabilistic projection approach in addressing the impacts of climate variability (change) on regional agricultural production and uncertainties.

Previous projections on maize productivity in China have had a wide range, depending on the emission scenarios, GCMs, and crop models used. For example, Wang and Lin (1996), using the CERES-maize model and three climate scenarios from doubled CO_2 simulations of three GCMs (i.e., GFDL, MPI, and UKMO; IPCC, 2001a), showed that at most investigated sites across China, simulated yields of both rainfed and irrigated maize would decrease under climate change scenarios. This was primarily due to increases in temperature, which could reduce the maize-growing period, particularly during grain-filling. Based on the CERES-maize model and three climate scenarios from doubled CO_2 simulations of three GCMs (i.e., GISS, GFDL, and UKMO), Fischer *et al.* (1996) showed that maize yield could decline in many countries with direct CO_2 effects, probably due to its lower response to the physiological effects of CO_2 on crop growth.

By using the CERES-maize model and the A2-based and B2-based climate scenarios from a regional climate model, Xiong *et al.* (2007) showed that maize productivity in the NCP would decrease by up to 25% under irrigation; however, rainfed maize productivity is projected to increase by up to 350% during the 2080s because of CO_2 fertilization effects. The simulations with CO_2 fertilization effects produced a 9–15% increase in yield compared to those without CO_2 effects in their study (Xiong *et al.*, 2007). Recent meta-analyses of free-air CO_2 enrichment studies indicate that, at 550 ppm [CO_2], yields increase under unstressed conditions by 10% to 25% for C3 crops, and by 0% to 10% for C4 crops (IPCC, 2007).

Integrated Assessment Results

Food security in China has long been a concern because of the challenges of population growth, water shortages, and loss of cropland through urbanization, soil degradation, and climate change. Tao *et al.* (2009) presented an integrated analysis of China's food demand and supply under the IPCC SRES A1, A2, B1, and B2 in 2020, 2050, and 2080, based on official statistics and future development scenarios. The analysis accounted for future socio-economic, technological, and resource developments, as well the impact of climate change. The study presented a covariant relationship between changes in cereal productivity due to climate change and the cereal harvest area required to satisfy China's food demand. The study also estimated the effects of (1) changing harvested areas on the productivity required to satisfy the food demand, (2) productivity changes due to climate change on the harvest area required to satisfy food demand, and (3) productivity and land-use changes on the population at risk of malnutrition.

Tao *et al.* (2009) suggest that China could be able to feed itself without disturbing the global food market in the 21st century, but whether the government will choose self-sufficiency or increased food imports may depend on the cost change, which

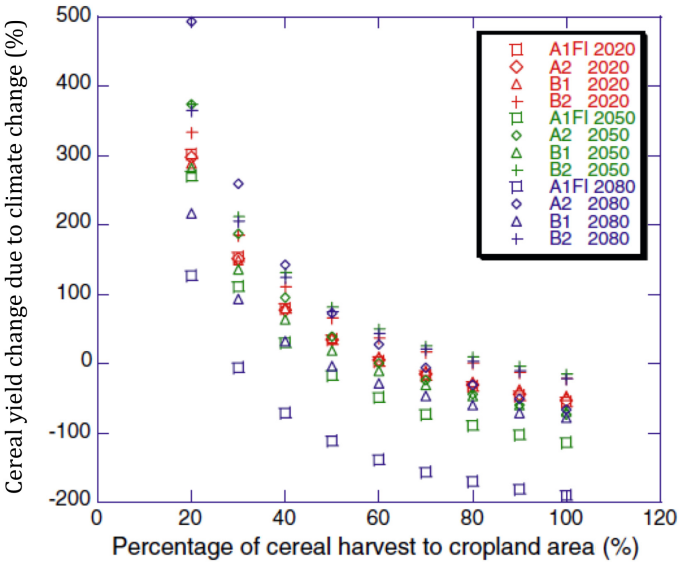


Fig. 3. The covariant relationship between cereal yield change and H/C to satisfy food demand in 2020, 2050, and 2080. H/C = ratio of cereal harvest area to total cropland areas.

remains unknown. Previous estimates (Parry *et al.*, 2004) showed that climate change (excluding the CO_2 fertilization effect) would decrease cereal yield in China by 2.5% to 5%, 2.5% to 10%, 0% to 2.5%, and 2.5% to 5% in 2020 under the A1FI, A2, B1, and B2 scenarios, respectively, compared with the 1990 value. Corresponding decreases of 5% to 10%, 5% to 10%, 5% to 10%, and 5% to 10% were projected for 2050, and 10% to 30%, 5% to 30%, 5% to 10%, and 5% to 10% for 2080 under the aforementioned four scenarios. Satisfying food demand under the A1FI, A2, B1, and B2 scenarios would require an H/C value (i.e., the ratio of cereal harvest area to the total cropland area) of at least 61% to 62%, 61% to 65%, 62% to 63%, and 79% to 81%, respectively, in 2020, versus values of 46% to 47%, 60% to 62%, 56% to 58%, and 88% to 92% in 2050 and 30% to 32%, 67% to 77%, 49% to 50%, and 83% to 87% in 2080 (Fig. 3).

By using the mean impact of climate change projected by Parry *et al.* (2004) for further estimation, and with H/C changing from 20% to 100%, the number of people at risk of malnutrition would change from 955 to 1,107 to –708 to 221 million in the 2020s, from 750 to 1,356 to –1,251 to 44 million in the 2050s, and from 381 to 1,823 to –1,906 to –125 million in the 2080s (Fig. 4). This means that if H/C were 100%, besides satisfying the food demand for all of its population, China could have a food surplus. The food surplus is an equivalent amount of food demand of 221 to 708 million people in the 2020s, 44 to 1,251 million people in the 2050s, and 125 to 1,906 million people in the 2080s. However, if H/C were only 20%, the number

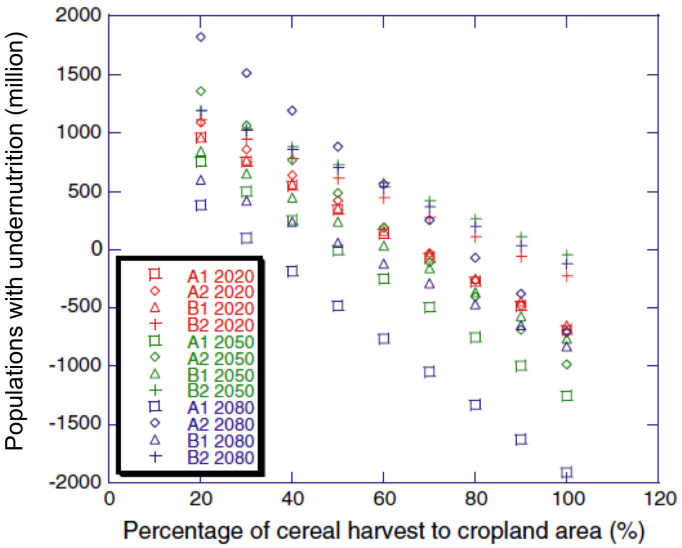


Fig. 4. Population at risk of malnutrition in relation to the ratio of harvest crop area and cropland area.

of people at risk of malnutrition would be 955 to 1,107 million in the 2020s, 750 to 1,356 million in the 2050s, and 381 to 1,823 million in the 2080s.

Evaluation of Potential Adaptation Strategies

Adaptation is a key factor that will shape the future severity of climate change impacts on food production. We need to evaluate the relative potential of adaptation strategies, and to develop effective adaptation strategies to cope with climate risk. Based on a large number of simulation outputs from the super-ensemble-based projections, our results show that without adaptation maize yield could decrease on average by 13.2% to 19.1%, and the ET during growing period could decrease by 15.6% to 21.8% during the 2050s, relative to 1961–1990.

In comparison with the experiment without adaptation, using high-temperature-sensitive maize varieties, simulated maize yields on average increased by 1.0% to 6.0%, 9.9% to 15.2%, and 4.1% to 5.6%, with early planting, fixing variety growing duration, and late planting, respectively. Simulated ET on average changed by 1.9% to 4.4%, 1.9% to 3.7%, and −2.9% to −0.7%, respectively.

In contrast, by using high-temperature-tolerant varieties, maize yield on average increased by −2.4% to −1.4%, 34.7–45.6%, and 5.7–6.1%, respectively. ET on average increased by 0.7% to 0.9%, 9.4% to 11.6%, and −0.4% to 0.2%, respectively. The spatial patterns show that the relative contributions of adaptation options can

be geographically quite different, depending on climate and variety. The biggest benefits would result from the development of new crop varieties that are high-temperature tolerant and have high thermal requirements. Other adaption options, such as cultivar renewal, and changes in agronomic management practices such as tillage, should be accounted for as well.

Conclusions and Next Steps

Climate change has had measurable impacts on agriculture in China in the past decades, and is projected to have a major impact on agriculture in the future. The impacts can have a large spatial difference. Although climate impact studies have made progress in recent years, there is still a long way to go. In the next steps, focus should be put on adaptations to climate change. New integrated agricultural system models that account for adaptations adequately should be developed and cross-sector integrated assessments should be conducted to design effective adaptation strategies.

References

Chavas, D. R., Izaurralde, R. C., Thomson, A. M., and Gao, X. (2009). Long-term climate change impacts on agricultural productivity in eastern China, *Agric Forest Meteorol.*, **149**, 1118–1128.

Food and Agriculture Organization of the United Nations (FAO) (2012). *FAO Statistical Databases*, Available at: http://faostat.fao.org. Accessed on 21 March 2014.

Fischer G., Frohberg, K, Parry M., and Rosenzweig, C. (1996). "The potential effects of climate change on world food production and security", in Bazzaz, F. and Sombroek, W. (eds). *Global climate change and agricultural production. Direct and indirect effects of changing hydrological, pedological and plant physiological processes*, FAO, Rome and John Wiley & Sons Ltd., Chichester.

Guo, R., Lin, Z., Mo X., and Yang, C (2010). Responses of crop yield and water use efficiency to climate change in the North China Plain, *Agric. Water Manage.*, **97**, 1185–1194.

IPCC (Intergovernmental Panel on Climate Change) (2001a). "Climate Change 2001: The Scientific Basis", in McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J., and White, K. S. (eds.), *Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

IPCC (Intergovernmental Panel on Climate Change) (2001b). "Climate change 2001: Impacts, adaptation and vulnerability", in McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J., and White, K. S. (eds.), *Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

IPCC (Intergovernmental Panel on Climate Change) (2007). *Climate Change 2007: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Parry M. L., Canziani, OF. Palutikof, J. P., van der Linden, P. J., and Hanson, C. E. (eds). Cambridge University Press, Cambridge, UK.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**, 235–265.

Lin, E., Xiong, W., Ju, H. Xu, Y. Li, Y., Bai L., and Xie L. (2005). Climate change impacts on crop yield and quality with CO_2 fertilization in China, *Philos. Trans. Roy. Soc. B*, **360**, 2149–2154.

Liu, Y. and Tao, F. (2013). Probabilistic Change of Wheat Productivity and Water Use in China for Global Mean Temperature Changes of 1, 2, and 3°C, *J. Appl. Meteorol. Clim.*, **52**, 130–146.

Matthews, R. B., Kropff, M. J., Horie T., and Bachelet, D. (1997). Simulating the impact of climate change on rice production in Asia and evaluating options for adaptation, *Agric. Syst.*, **54**, 399–425.

Mo, X., Liu, S., Lin Z., and Guo, R. (2009). Regional crop yield, water consumption and water use efficiency and their responses to climate change in the North China Plain, *Agric. Ecosyst. Environ.*, **134**, 67–78.

Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M., and Fischer, G. (2004). Effects of climate change on global food production under SRES emissions and socio-economic scenarios, *Global Environ Change*, **14**, 53–67.

Piao, S. L., Ciais, P., Huang, Y., Shen, Z. H., Peng, S. S., Li, J. S., Zhou, L. P., Liu, H. Y., Ma, Y. C., Ding, Y. H., Friedlingstein, P., Liu, C. Z., Tan, K., Yu, Y. Q., Zhang T. Y., and Fang J. Y. (2010). The impacts of climate change on water resources and agriculture in China, *Nature*, **467**, 43–51.

Shen, S., Yang, S., Zhao, Y., Xu, Y., Zhao, X., Wang, Z., Liu J., and Zhang, W. (2011). Simulating the rice yield change in the middle and lower reaches of the Yangtze River under SRES B2 scenario, *Acta Ecol. Sinica*, **31**, 40–48.

State Environmental Protection Administration (2003). *Progress Report of Trade Liberalization in the Agriculture Sector and the Environment, With Specific Focus on the Rice Sector in China*. Available at: http://www.unep.ch/etb/events/Events2003/pdf/FinalDraftofChinaStudy.pdf. Accessed on 21 March 2014.

Tao, F., Hayashi, Y., Yokozawa, M., Zhang Z., and Sakamoto, T. (2008). Global warming, rice production and water use in China: Developing a probabilistic assessment, *Agric. Forest Meteorol.*, **148**, 94–110.

Tao, F., Yokozawa, M. and Zhang, Z. (2009a). Modeling the Impacts of Weather and Climate Variability on Crop Productivity over a Large Area: A New Process-based Model Development, Optimization, and Uncertainties Analysis, *Agric. Forest Meteorol.*, **149**, 831–850.

Tao, F. and Zhang, Z. (2010). Adaptation of maize production to climate change in North China Plain: Quantify the relative contributions of adaptation options, *Eur. J. Agron.*, **33**, 103–116.

Tao, F. and Zhang, Z. (2011). Impacts of climate change as a function of global mean temperature: Maize productivity and water use in China, *Clim. Change*, **105**, 409–432.

Tao, F. and Zhang, Z. (2013). Climate Change, High Temperature Stress, Rice Productivity and Water Use in Eastern China: A New Super-ensemble-based Probabilistic Projection, *J. Appl. Meteorol. Clim.*, **52**, 531–551.

Tao, F. Zhang, Z., Liu, J., and Yokozawa, M. (2009b). Modeling the Impacts of Weather and Climate Variability on Crop Productivity over a Large Area: A new super-ensemble-based probabilistic projection, *Agric. Forest Meteorol.*, **149**, 1266–1278.

Tao, F., Zhang, Z., Zhang, S., Zhu Z., and Shi, W. (2012). Response of crop yields to climate trends since 1980 in China, *Clim. Res.*, **54**, 233–247.

Wang J. and Lin, E. (1996). The impacts of potential climate change and climate variability on simulated maize production in China, *Water Air Soil Pollut.*, **92**, 75–85.

Xiong, W., Conway, D., Jiang, J., Li, Y. Lin, E. Xu, Y., Hui J., and Calsamiglia-Mendlewicz, S. (2008). *Future cereal production in China: Modelling the interaction of climate change, water availability and socio-economic scenarios*. Available at: http://www.uea.ac.uk/polopoly_fs/1.147096!Xiongetal2008Report-Future-cereal-production-Interaction.pdf. Accessed on 21 March 2014.

Xiong, W, Matthews, R., Holman, I, Lin, E., and Xu, Y (2007). Modeling China's potential maize production at regional scale under climate change, *Clim. Change*, **85**, 433–451.

Yao, F., Xu, Y., Lin, E., Yokozawa, M., and Zhang, J. (2007). Assessing the impacts of climate change on rice yields in the main rice areas of China, *Clim. Change*, **80**, 395–409.

Zhai, P. M. and Pan, X. H. (2003). Trends in temperature extremes during 1951–1999 in China, *Geophys. Res. Lett*., **30**, 1913.

Zhai, P. M., Zhang X. B., and Pan, X. H. (2005). Trends in total precipitation and frequency of daily precipitation extremes over China, *J. Clim*., **18**, 1096–1108.

Section IV

Capacity Building and Outreach

This page intentionally left blank

Chapter 13

AgMIP Training in Multiple Crop Models and Tools

Kenneth J. Boote[1], Cheryl H. Porter[2], John Hargreaves[3], Gerrit Hoogenboom[4], Peter Thorburn[5], and Carolyn Mutter[6]

[1]*University of Florida, Gainesville, FL, USA*

[2]*University of Florida, Gainesville, FL, USA*

[3]*Agricultural Productivity Flagship, CSIRO, Brisbane, Australia*

[4]*Washington State University, Prosser, WA, USA*

[5]*Agricultural Productivity Flagship, CSIRO, Toowoomba, Australia*

[6]*Columbia University, New York, NY, USA*

Introduction

The Agricultural Model Intercomparison and Improvement Project (AgMIP) has the goal of using multiple crop models to evaluate climate impacts on agricultural production and food security in developed and developing countries. There are several major limitations that must be overcome to achieve this goal, including the need to train AgMIP regional research team (RRT) crop modelers to use models other than the ones they are currently familiar with, plus the need to harmonize and interconvert the disparate input file formats used for the various models. Two activities were followed to address these shortcomings among AgMIP RRTs to enable them to use multiple models to evaluate climate impacts on crop production and food security. We designed and conducted courses in which participants trained on two different sets of crop models, with emphasis on the model of least experience. In a second activity, the AgMIP IT group created templates for inputting data on soils, management, weather, and crops into AgMIP harmonized databases, and developed translation tools for converting the harmonized data into files that are ready for multiple crop model (hereafter termed *multi-model*) simulations. The strategies for creating and conducting the multi-model course and developing entry and translation tools are reviewed in this chapter.

Participants came to the multi-model training course with data that they had already tested and simulated with their favored model; an iterative process commonly referred to as model "calibration". Following lectures on the general principles of crop growth and soil–water balance common to both models, the participants used the IT tools to convert the files into the alternate model, and worked with the experts of those models to step through a calibration process with the new model. This provided each crop modeling team with a second simulation of production associated with the same farmer field survey data.

The course was clearly valued by the participants, as it was a mid-project achievement that allowed them to complete the multi-model simulations as part of the integrated assessment that they were doing in their regional research teams (see Part 2, Chapters 1–12 in this volume). The designation and use of trainers and AgMIP resource persons was very valuable, as they mentored and assisted small working groups, the number of which exceeded the number of instructors available. Furthermore, the course was a good test-bed for the IT tools, providing evaluation that led to improvements in the conversion tools for creating model-ready files.

History of Crop Modeling Courses

Training in crop modeling has followed several pathways. A common pathway over the past 30–40 years has been one-on-one training during graduate or post-doctoral programs, or during targeted visits with crop modeling experts. A second pathway has been structured training courses in which a number of trainees come to a location and follow a five to eight day course of lectures, hands-on training, and exercises. The first of these types of one-week training courses was conducted in 1981 by the Department of Theoretical Production Ecology, Wageningen Agricultural University, the Netherlands. The senior author was privileged to attend that course. That course was connected to the 1982 book edited by Penning de Vries and van Laar (1982).

University of Florida crop modelers (J. W. Jones, K. J. Boote, and G. Wilkerson) conducted their first crop modeling course at the University of Florida in 1985, with a similar one-week format. After that initial start, a larger group of crop modelers associated with the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project proceeded to conduct six to ten day crop modeling courses at various sites in the US and around the world, beginning with Taiwan in 1986 and the International Center for Research in the Semi-Arid Tropics (ICRISAT) in 1987. Crop modeling courses with the Decision Support System for Agrotechnology Transfer (DSSAT) software have continued since on a nearly annual or biannual basis (Hoogenboom *et al.*, 2010; Jones *et al.*, 2003). The course was offered 20 times in the USA since 1985, and international courses were taught

Table 1. History and locations of DSSAT training courses since 1985.

Country	Year of training course
United States	1985, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2002, 2004, 2006, 2008, 2009, 2010, 2011, 2012, 2013, 2014
Taiwan	1986
India	1987, 2010, 2011, 2012
Senegal	1989, 2014
Venezuela	1989
Republic of South Africa	1990, 1995
Hungary	1991, 1992
Canada	1997
Egypt	1998, 1999
Togo	1998
Thailand	2003, 2004, 2007, 2013, 2014
Tanzania	2004
Ghana	2005
Argentina	2006, 2007
People's Republic of China	2006
Kenya	2007
Namibia	2007
Malaysia	2009
Spain	2009
Barbados	2012

in Taiwan, India, Senegal, Venezuela, Republic of South Africa, Hungary, Canada, Togo, Ghana, Egypt, Tanzania, Argentina, the People's Republic of China, Kenya, Namibia, Malaysia, Barbados, Spain, and Thailand (Table 1). The number of participants ranged from 10–60 people, usually 20–30 at a time. The book edited by Tsuji, Hoogenboom, and Thornton (1998) serves as the textbook for the DSSAT crop modeling courses. More than 1000 students have been trained over this period.

The Dutch crop modelers conducted similar training courses on a regular basis, especially during the Dutch government-funded project, Simulation and Systems Analysis for Rice Production (SARP) in Asia during the mid-1980s to the mid-1990s (ten Berge, 1993). In that project, the Center for Agrobiological Research and Wageningen Agricultural University linked with the International Rice Research Institute and 16 national agricultural research centers in Asia, to conduct systems analysis and simulation modeling, mostly on rice, by using the SUCROS model (Penning de Vries *et al.*, 1989). Training courses were conducted at Wageningen and at international sites, following the template of the Penning de Vries and van Laar (1982) book, along with training in use of SUCROS and use of the Continuous Systems Modeling Program (CSMP) language.

Other models and modeling groups such as the Agricultural Production Systems Simulator (APSIM; Keating *et al.*, 2003), EPIC (Izaurralde *et al.*, 2006; Williams *et al.*, 1989), and CropSyst (Stöckle *et al.*, 2003) hold somewhat shorter in-house training sessions for one to ten people at a time, generally at their research sites. The CropSyst group uses web-based training approaches. APSIM conducts two-day training sessions several times per year in Australia, mostly on operational aspects of the model software. Many Australian international agricultural research projects include five-day APSIM workshops in-country for 15–20 persons as required. These courses are tailored for the regions (i.e., Africa and Asia) in which the project members operate, and usually consist of three days of hands-on activities with science theory and understanding of the dynamics of the processes producing the simulation results, followed by two days of small-group activities using simulations to explore local issues and strengthen simulation skills. A half-day of instruction on soil sampling is sometimes conducted. Other APSIM international training activities include participatory crop modeling training that targets agricultural researchers proficient in the use of APSIM for adding value to on-farm research and extension focusing on climate change adaptation and crop production. The first international APSIM course was held in 1997 at the ICRISAT center as part of a joint project entitled "Collaboration on Agricultural Resource Modeling and Applications in Semi-Arid Tropics".

Approaches Followed in Crop Modeling Courses

The approaches in the DSSAT and Dutch-SARP crop model training courses followed a template that included some lectures interspersed with hands-on use of the software and model interfaces, along with exercises. The lectures covered principles of crop phenology, crop carbon (dry matter) balance, crop soil–water balance, soil–plant N balance, model calibration, model sensitivity analyses, etc. The hands-on training with the software included exercises to demonstrate data entry, proper creation of weather, soils, and management files, model calibration, model simulation, and data analyses. Trainees were encouraged to come with their own data and to develop a special topic or exercise with their data. If they did not have data, students were given topics in which they were to create model-ready files to conduct multi-year simulations of various treatments or crop sequences. Results were then analyzed to evaluate how various treatments affected crop yields, irrigation requirements, seasonal evapotranspiration, soil C dynamics, fertilizer N response, N leaching, economic returns, and optimal economic decisions, etc.

The Dutch government-funded SARP project, particularly in its later phases, discovered that sustained follow-through was very important. Project organizers established and funded a program for field-oriented scientists from Asia for one-year of formal training that involved about half-time on field data collection and half-time on crop modeling (ten Berge, 1993). The African Network for Soil Biology

and Fertility (AfNet) Project (Bationo *et al.*, 2012) established a similar program in Africa. In this multi-year-funded project, African scientists participated in an introductory crop modeling workshop, followed by field data collection on a topic that could be further analyzed by crop model simulations, followed by a workshop with the models and their data, and then a third workshop to present their final results that ended up as written papers being published in a book (Bationo *et al.*, 2012). A similar approach is followed by Australian projects that make use of the APSIM systems modeling as an analysis tool.

APSIM workshops are conducted in Australian projects in which simulation is required as an analysis tool for components of the project (Keating *et al.*, 2003). Most experiences are published in project reports by the project sponsors (e.g., Australian Center for International Agricultural Research, Australian Agency for International Development, ICRISAT, and Rockefeller Foundation).

Reasons for Multi-model Course Taught by AgMIP Scientists

The AgMIP project has a strong focus on multi-model simulations to evaluate impacts of climate scenarios on agricultural production, similar to the use of multiple global climate models for prediction of future climate (Rosenzweig *et al.*, 2013). The concept of multi-model use is that the ensemble of several models may be a better predictor than any given single model, as already learned by the AgMIP wheat teams (Asseng *et al.*, 2013), the AgMIP maize teams (Bassu *et al.*, 2014), the AgMIP rice teams, and AgMIP sugarcane modelers. As a result, projects using AgMIP protocols require the application of at least two crop models. This goal can be achieved by bringing together scientists with expertise in different models to analyze datasets from the region of interest. However, in many regions, especially in developing countries, there are few scientists proficient in crop modeling and RRTs may have scientists proficient with just one model. Thus, there is a need to encourage these crop modelers to learn to use more than one crop model, as well as to collaborate with others in multi-model activities.

Specifically, participating scientists in the regional teams funded by the UK Department of Foreign International Development (DFID) wished to use multiple crop models (DSSAT and APSIM at minimum) to simulate yields relative to farm survey data collected by socio-economists as a way to evaluate climate impact on farm-to-farm variability in production, and subsequently to conduct integrated production–economic assessment. Therefore, AgMIP leaders developed training courses for the regional team participants in which multi-model training/use were emphasized. In the AgMIP Handbook protocol (see Part 1, Appendix 1 in this volume and Rosenzweig *et al.*, 2014) of the DFID-funded regional integrated assessment projects, economists use the simulated farm-to-farm variability and simulated climate change ratio (R, the yield under 30-year future climate divided by yield

under 30-year current climate for each farm). The value of *R* is multiplied by the present farm survey yield as part of an integrated assessment of winners and losers among the farmers as affected by climate change and technological adaptation. The value of *R* for a given field may differ among crop models, thus representing a range of uncertainty regarding the potential effect of climate change on crop production.

Other reasons for multi-model courses are that participants want to learn about crop models other than the model they currently use. Participants are interested in seeing how other models take different approaches to address soil processes, crop management, and cultivars. The crop modelers can translate their experiences from one model to the next, because the concepts are often similar even if the coefficients and model structure may be different. Although the crop models and the software interfaces may differ among different modeling groups, the basic principles are similar relative to use of weather, soils, and management data. Likewise, crop growth and yield measurements are similar in use and purpose, despite different variable naming and different graphical and text comparisons of simulated versus observed values.

Finally, modelers understand that all models need further calibration and development to improve their simulation of biophysical field conditions. Learning about how different models simulate response to the biophysical environment provides rich stimulus for considering how to further improve model processes themselves. Differently parameterized models typically yield different results for the same input data — deciphering why this happens is an important learning experience for modelers, who must be able to assess and interpret outputs — all of which yield information (or limitations) as to how models simulate agricultural systems, and why they sometimes "fail".

An important reason for the AgMIP multi-model course was to introduce and teach the crop modelers how to use the newly developed IT tools (see also Part 1, Chapter 6 in this volume) for data entry and conversion. The alternative would have been for students to learn both the DSSAT- or APSIM-specific tools for defining crop management in the models based on the farm survey data, but this would not have accomplished the objective of having the same data entered once with templates into the AgMIP-harmonized format and being translatable into the files ready to run for both models. For that reason, the IT tools were a strong focus for at least three days of the training course. AgMIP is motivated to help create tools that encourage the use of multi-model approaches by easing the ability to move among models, an activity that requires close collaboration with the model developers themselves (see also Part 1, Chapter 6 in this volume).

Planning and Preparations for the Multi-model Training Course

Potential participants were surveyed to learn of their prior experience in crop modeling with their currently used model and to designate which model they wanted to

learn more about. An important requirement was that participants have prior experience with at least one crop model, as this course was not designed to be a beginners' course.

Prior to the training course, an email was sent to participants requesting that they: (1) come with their own portable laptop computer, (2) identify and come with sentinel site experimental data following AgMIP sentinel site data standards (Kersebaum *et al.*, 2014) that had a minimum amount and quality of measurements of crop life-cycle phenology, final biomass, final yields, modest growth analyses, along with site-specific weather, soils and crop management inputs in order to simulate crop growth, for which they were already running their current model and for which they would calibrate cultivar coefficients with a new model; (3) come with the farm survey yield data (as well as associated management and soils data), which they would enter during the course; and (4) come with 30 years of historical "baseline" weather data for the farm survey region, including weather for the actual farm survey years.

The 30-year current baseline weather data were to be modified by their climate scientist colleagues to produce a given defined climate scenario by using the delta method. During the course they followed-up with crop simulations of the individual farm sites in order to calculate the climate change ratios to provide to their economist collaborators, by following protocols of the AgMIP Handbook (see Part 1, Appendix 1 in this volume and Rosenzweig *et al.*, 2014).

Instructors and Train-the-Trainers

An important goal of AgMIP is capacity-building and development of regional crop modeling capability, to include facilitating individuals with the potential to become future instructors and trainers of other crop modelers. Prior to the multi-model training course, the instructors (K. J. Boote, C. H. Porter, J. Hargreaves, and G. Hoogenboom) and P. Thorburn engaged AgMIP coordination in a process of candidate selection, with selectees demonstrating good crop modeling skills, good leadership, and good teaching and mentoring potential, with appropriate regional and gender representation (five developing countries and two women). The selectees included D. S. MacCarthy (Ghana), D. M. Kadiyala (India), D. Fatondji (Niger), N. Subash (India), G. Baigorria (US), P. Masikati (Zimbabwi), B. Singh (India), and A. Wajid (Pakistan). During the training course, these individuals took an active role to mentor and assist their colleagues on particular models and/or crop expertise that they had. The instructors provided additional guidance and advice to these designated individuals, with the expectation that they would return to their region or university and help train other crop modelers in their current team, university, or region.

Fig. 1. Initiation of multi-model training course activities in the learning systems unit at the ICRISAT, Andra Pradesh, India.

Conducting the Course and the Course Syllabus

The course was conducted at two locations using the same curricula and overall plan: During March 18–22, 2013 at Hotel Annapurna, Kathmandu, Nepal (about ten students attended), and during March 25–29, 2013 at the ICRISAT center, Andhra Pradesh, India (about 40 students attended, see Part 2, Appendix 1 in this volume for the ICRISAT Workshop report). To the extent possible, trainers-in-training attended both events. This allowed for close interaction and advancement of their own capabilities in the first, smaller event — and provided immediate opportunity to utilize their skills as trainers in the second, larger event. The photo (Fig. 1) shows the initiation of the second course, held at the Learning Systems Unit at ICRISAT. Course activities for the AgMIP Multiple Crop Model Training Program are described in the syllabus (Annex 1 at the end of this chapter). In addition, participants were provided with the *Guide for Regional Integrated Assessments: Handbook of Methods and Procedures, Version 4.0*, specifically Appendix 2, *Crop Model Simulations for Integrated Assessments: User's Guide*, available in the AgMIP Handbook (see Part 1, Appendix 1 in this volume and Rosenzweig *et al.*, 2014). The latter contain the AgMIP protocols for using the IT tools for entering farm survey yield data in template files, creating the data overlay files to provide assumptions for information missing from survey management and soils, and conducting the crop model simulations to produce results to pass on to the economists for the integrated biophysical and socio-economic assessment.

During the first day of the course, we introduced the integrated assessment goals, and then gave an overview of DSSAT and APSIM crop models, specifically how phenological development, growth and yield, soil–water dynamics, and genetic coefficients are formulated in each model. Principles of genetic coefficient calibration were introduced. Initially, all participants were together in the same room learning about both models. Late in the afternoon of the first day, participants installed their newly chosen models, and learned the procedures for inputting new crop, soil, management, and weather data for the purpose of estimating genetic coefficients from the sentinel site experiment data.

On day 2 of the course, after one plenary lecture on soils and crop management aspects, we separated into two parallel sessions, with one group learning DSSAT and the other learning APSIM. During the rest of this day, students worked with their new crop model, and entered soil, weather, management, and crop observation data, which they used to estimate the model-specific genetic coefficients for their cultivar from their sentinel site experiment data. As necessary, small-group model-specific lectures were conducted to address model-specific issues related to genetic coefficient calibration.

On day 3, the students completed their calibration of genetic coefficients for their new crop model, created visuals, and presented their results per team in a plenary session near mid-day. After each presentation, we discussed what had been done and gave recommendations for improvement.

In the afternoon of day 3, the AgMIP IT tools — survey data template, data overlay files, and QuadUI (the desktop application for data translation) — for entering farm survey data were introduced and explained (see also Part 1, Chapter 6 in this volume). The participants then began to enter their farm survey yield and management information into the AgMIP template spreadsheets.

On day 4, there was a plenary lecture on the goals of AgMIP integrated assessment for analyzing farm production as well as methods for analyzing farm survey data and simulated production. We discussed proper use of AgMIP tools to complete entry of field survey data as well as creation of Data Overlay for Multi-model Export (DOME) files for input of missing initialization and management information. We assisted the participants in use of the AgMIP tools to convert field survey data into model-ready files. We advised on the need to verify their inputs (management, soils, initial conditions, and cultivar) and assisted in getting the crop models to run with their data.

We assisted in analyzing simulated results and in computing the mean and plotting the cumulative probability of exceedance for the observed farm survey yields and model-simulated yields on the same graph. Figure 2 illustrates the probability of exceedance of a given yield level for farmer survey yields, compared with the yields simulated by DSSAT and APSIM for peanut fields near Nioro, Senegal in

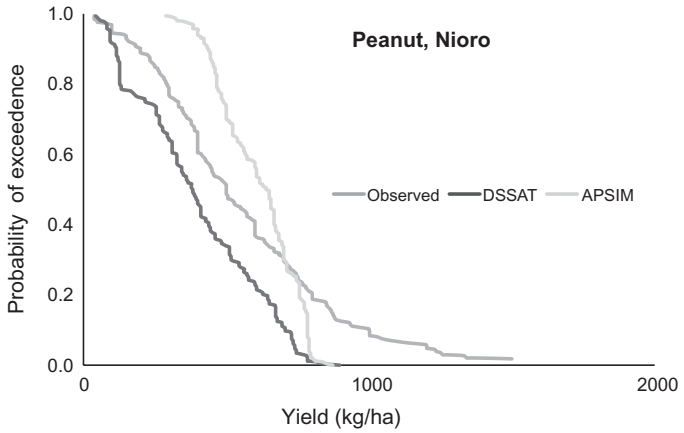


Fig. 2. Probability of exceedance of a given yield level among farmer survey fields, DSSAT simulations, and APSIM simulations for peanut fields near Nioro, Senegal in 2007 (courtesy of CIWARA team in Part 2, Chapter 2 in this volume).

2007 (courtesy of AgMIP's Western Africa team, CIWARA; see also Part 2, Chapter 2 in this volume). The farmer survey fields generally have greater yield variation, possibly because failures from pest, disease, and weed problems in farmer fields mean that the models do not simulate, as well as insufficient variation of soils (water/productivity) assigned to the model simulations. We discussed the need to evaluate the simulated and observed distributions and to understand the causes for model failure to predict accurately the mean as well as the high or low tails of the cumulative probability of exceedance. In some cases, these were caused by simple errors in setting up of the models and these were resolved. In some cases, soil initial-condition assumptions related to soil water and soil organic carbon pools had major effects on the distributions obtained.

Although the economists had requested that no external bias adjustments be made (because they only needed the value of climate change ratio (R) to be predicted to transform the observed yield in each farm), there were often serious bias-influencing input issues relative to initial soil water, initial soil mineral N, soil organic C pools, and residue assumptions that were made (because such information was missing from the farm survey data). Consistent rules for bias-adjusting corrections were suggested to facilitate realistic yield levels and distributions for the region that would be believed by stakeholders. At the same time students were cautioned that corrections needed to be limited to broad classes of problems for multiple farms, and in no case were adjustments allowed to be made on a "farm-by-farm" basis in absence of data. The reason for this caution was that at least one group had previously micro-calibrated inputs for every single field (without true evidence of input variation) to exactly mimic the observed yield for each and every survey field.

On day 5, there was a plenary lecture on seasonal analyses with multiple weather years that was presented as a way to analyze the risk of weather variability. Then the student-modelers moved on to conduct multi-year simulations using the seasonal strategy tools that provide consistent rules of auto-sowing to be set up, since the "single year" farmer survey sowing dates were potentially inappropriate for future climate conditions. Multi-year simulations were run for both baseline "current" weather and at least one future climate change scenario. Participants were shown how to use the IT tools to place the simulated yields (current and future) into the AgMIP crop model output (ACMO) harmonized format, ready for use by the agricultural economists (see also Part 1, Chapter 6 in this volume). Mean 30-year yield per farm was computed for the baseline and for future climate, for use in computing the value of R for each farm. The students prepared presentations of their results that were reported in a joint session that facilitated discussion and recommendations. The course ended with participant feedback of what worked and what did not work.

Experiences during the Course: What Worked and What Did Not

Some of the participants were not as experienced with crop modeling as presumed when setting up these workshops. All participants should have had a full basic training course prior to coming to this multi-model course. Because of time limitations and the need to use two crop models along with new IT Tools, this multi-model course intentionally did not include the basic lectures or hands-on training exercises typical of beginners' crop modeling courses. That created some frustration and lack of effective learning for some participants who came with insufficient required experience.

The number of participants also made a difference. There were ten students in Nepal and 40 at ICRISAT, and the latter number stretched the training capacity of the four instructors despite help from the eight designated "train-the-trainers" in the role of instructor–advisors. There was a relative deficiency in APSIM instructor support, although five of the trainers had some APSIM experience. Train-the-trainers provided expertise to solve many issues along the way, considering that there were only four primary lecturers and that many IT tool issues came up along with the typical crop model issues. The train-the-trainers also provided expertise on alternate crops. Because of several different crops and different country teams (six teams at ICRISAT), students evolved into many small working groups, which is another reason that multiple instructors and trainers with expertise in different models and crops were needed.

The installation and setup of the DSSAT and APSIM models worked well on the individual students' laptop computers, with a few exceptions due to international language operating systems and Macintosh computers. There were some difficulties with the use of the new IT tools. The rice models required additional management

inputs to characterize paddy management (puddling, bund height, flooding depth, percolation rate, etc.), which had not yet been programmed into the data translators for DSSAT or APSIM. By the time of the second one-week course held at ICRISAT, these problems were mostly solved.

Mid-week, we had separate break-out sessions of 20–30 minutes in which instructors met separately with each modeling team, to look in detail at the model input files for simulations, to verify correct entry and use of sentinel site data for calibrating cultivar coefficients, and to set up model assumptions for farm survey fields relative to irrigation, initial soil water, initial nitrate and ammonium, and soil organic C pools (if the latter were to be used). In these sessions, the DSSAT modelers worked with DSSAT instructors and APSIM modelers worked with the APSIM instructor. This double-check was very important and valuable to all, despite not being listed as a course topic. While inspecting the model input files, we discovered many issues such as not setting initial conditions for soil water, crop residue, nitrate and ammonium, and failure to simulate rice as paddy. Some teams "micro-calibrated" to each farmer field and this was strongly discouraged. Some did the climate scenarios incorrectly. These were issues that were not apparent in the preliminary written reports of the teams, and therefore required the re-doing and re-running of their original simulations. Hands-on-evaluation of model *input files* by model experts *must* be a part of all training courses that have viable simulations as an output.

The IT tools were successfully used for template entry, and conversion of survey data to DSSAT ready-to-run files worked for maize, millet, and wheat. Conversion to files ready to run for the DSSAT CSM-CERES-rice did not work initially because of limitations related to paddy water management (puddling, percolation rate, bund height, and water height). These were solved during the multi-model training courses. The tools to convert to APSIM-ready files worked only for maize. The course was successful in being a "beta" test-bed in which to identify issues that the AgMIP IT team needed to resolve for wheat, sorghum, and millet model files; these issues were resolved by the end of the two weeks. The APSIM-rice issues were solved later.

A shortcoming of this course was that no one successfully parameterized the soil carbon modules, whether the DSSAT CSM-CENTURY's stable soil carbon pool (SOM3) or the APSIM's fraction inert soil carbon pool. The CENTURY soil carbon option was generally not used despite encouragement to use it, and it was never used for the rice models. So, a conclusion here is that the correct setting of soil carbon pools is a major difficulty in the crop models, and that this may limit the ability to accurately predict production of non-legumes under degraded soil conditions.

Another short-coming is that there was insufficient time to discuss the effects of climate change scenarios, and specifically the climate change ratio. The five-day course was too short. We also lacked time for sufficient discussion and evaluation of

the probability of exceedance distributions (and means) for simulated and observed farm survey yields, despite having a final report-back on those topics on the last day. The report-back on genetic coefficient calibration early in the week worked well.

Feedback at end-of-day and at start of every morning was valuable for purposes of discovering how far individual groups had progressed and to solve any problems that may have arisen. The majority of the project-funded teams managed to calibrate genetic coefficients for both crop models, and accomplished their farm survey simulations for at least DSSAT. Deficiencies in the APSIM data translator prevented completion of APSIM simulations for rice, wheat, and millet crops. The teams learned enough that they could return to their countries and complete the simulations later, after the data translation issues were solved.

Conclusions and Next Steps

The AgMIP Multiple Model Course was clearly needed and valued by the crop modeling participants, as it allowed them to complete the multi-model simulations for the integrated assessment that they were doing in their RRTs. The course generally went smoothly, especially in Nepal, where the number of students was small (about ten) and the crops fewer. At the ICRISAT center in India, the facilities were good, but the auditorium setting and the number of students (40 or more) with diverse regions and more crops simulated, made the course more difficult to handle. More of the participants at ICRISAT were beginners to crop modeling. Future courses with multi-model agendas will need to ensure better beginners' training or vetting of the participants. The use of trainers and AgMIP resource persons was very valuable, as they assisted with the many small working groups that exceeded the number of instructors available.

The IT tools generally worked as planned, although mid-course improvements in the conversion tools were needed in order to create model-ready files for DSSAT CSM-CERES-rice, and for nearly all APSIM crops with the exception of maize. In that sense, the course provided a useful opportunity to test, refine, and improve the IT tools.

The need for continued training in crop modeling is highlighted by this course. Distance-training modules can be designed, but will require coordination with DSSAT and APSIM modeler groups who have the training materials. The use of the IT tools for multi-model use and translation of data formats from one model to the other could be set up as a distance-training module within AgMIP. Another approach is to encourage the new train-the-trainers to lead crop model training courses in their own regions and institutions.

The participants in the multi-model training were requested to identify specific actions planned after this course to include: (1) How will the multiple-model

capability be used in research that is under way? (2) Who would go back and host training sessions and with what institution? (3) What opportunities exist for leveraging multi-model capabilities in related work that falls outside of the AgMIP area? (4) What opportunities exist for introducing materials of multiple-crop-model methods into institutional practice guides or university course curricula?

In conclusion, the AgMIP Multiple Crop Model Course successfully met its objective of training crop modelers on two different models; this in turn allowed the regional project teams to meet their integrated assessment goals. The experience with this course also provided ideas for improvements in future multi-model training courses.

Annex I

AgMIP Multiple Crop Model Training Program

25–29 March 2013

ICRISAT

Andhra Pradesh, India

Program

Day/Date/ Time	Session	Facilitator
Day 1 Monday 25 March	**Overview:** Overview of DSSAT and APSIM crop models, specifically how phenological development, growth and yield, and soil water dynamics are modeled, and overview of the genetic coefficients needed for each model.	
0800-0830	Registration	
0830-0900	**Plenary Session** — Welcome	G Dileepkumar
	Introductions — each participant	All
	About AgMIP Project	Peter Craufurd
0900-0940	Course objectives, overview of program	Ken Boote
	A broad overview and discussing APSIM, DSSAT including AgMIP Integrated Assessment perspective	
0940-1000	Group Photo, Tea/Coffee break	
1000-1100	Overview of DSSAT growth and phenology	Ken Boote
1100-1200	Overview of APSIM growth and phenology	John Hargreaves
1200-1300	Lunch	
1300-1400	Principles of genetic coefficient calibration	Ken Boote

(*Continued*)

(*Continued*)

Day/Date/ Time	Session	Facilitator
1400-1430	Discussion — Issues with data and calibration	Instructors
1430-1445	Tea/Coffee Break	
1445-1700	**Parallel Sessions: DSSAT and APSIM Groups** Model installation and operation Example calibration of genetic coefficients Procedures for inputting new crop, soil, management, weather data. Entering new experiments for use in estimating GCs	
1700-1730	**Plenary Session:** Discussion of progress, issues	Instructors
1830	Welcome Dinner	
2030-2130	**Optional Session** for review and refinement of data, prior calibrations, methods	
Day 2 Tuesday 26 March	**Overview:** Consideration of soils and management; parallel DSSAT and APSIM sessions; exploration of soil, weather, management, and crop data; understanding model-specific genetic coefficients; feedback on progress and issues; optional evening session for review and practice.	
0830-0930	**Plenary Session:** Initializing soils and management for reliable simulations	Cheryl Porter
0930-1200	**Parallel Sessions: DSSAT and APSIM Groups** Work with participant's data (use AgMIP IT tools as available to convert files); review their prior simulations. Soil Weather Management Crop observations Verifying inputs and simulations	
1200-1300	Lunch	
1300-1700	**Continue Parallel Sessions: DSSAT and APSIM Groups** Model-specific genetic coefficient lectures Calibrate model for genetic coefficients	
1700-1730	**Plenary Session:** Discussion of progress and issues	
1930-2100	**Optional Session** for review, work, and practice	
Day 3 Wednesday 27 March	**Overview:** Continue parallel sessions, undertaking genetic coefficient calibrations; present findings in plenary; utilize AgMIP tools and procedures for integrated assessment; initiate field survey data analysis; optional evening session for review, work and practice.	
0830-1200	**Parallel Sessions: DSSAT and APSIM Groups** Participants complete estimation of genetic coefficients Prepare summary graphs, report	
1200-1300	Lunch	
1300-1400	**Plenary Session:** Presentation of genetic coefficient calibrations (5 minutes each)	
1400-1445	Discussion of calibrations, feedback, recommendations to teams for follow-up	Instructors
1445-1500	Tea/Coffee Break	
1500-1530	**Plenary Session:** Goals of AgMIP integrated assessment (creating economic inputs & results for DSS)	Ken Boote

(*Continued*)

(*Continued*)

Day/Date/ Time	Session	Facilitator
1530-1630	AgMIP tools and procedures for integrated assessment Use AgMIP Tools to complete entry of field survey data Create Overlay for "missing" initialization/management Convert field survey data into model-ready forms	Cheryl Porter
1630-1700	**Individual Study in Plenary:** Participants working on their field survey data	
1700-1730	Discussion	
1930-2100	**Optional Session** for review, work, and practice	
Day 4 Thursday 28 March	**Objectives:** AgMIP integrated assessments; analyzing farm production; using AgMIP tools to handle missing data; verify inputs and simulate productivity; analyze, bias correct, interpret, question reliability/believability of findings.	
0830-0900	**Plenary Session:** Methods for analyzing farm survey observed and simulated production	Ken Boote
0900-0915	Discussion	
0915-0930	Tea/Coffee Break	
0930-1200	**Parallel Sessions: DSSAT and APSIM Groups** Verify inputs (management, soils, IC, cultivar) & simulate Analyze simulated results, mean, cumulative probability Compute bias and determine if adjustments are needed Are results reliable? Believable?	
1200-1300	Lunch	
1300-1700	**Parallel Sessions: DSSAT and APSIM Groups** Verify inputs (management, soils, IC, cultivar) & simulate Analyze simulated results, mean, cumulative probability Compute bias and determine if adjustments are needed Are results reliable? Believable?	
1700-1800	**Plenary Session:** Discussion of problems and issues	
Day 5 Friday 29 March	**Objectives:** Seasonal analyses; multi year simulations, ACMO files, collaborative preparation of reports (for presentation by selected trainees); presentation; feedback on training.	
0830-0900	**Plenary Session:** Seasonal analyses with multiple weather years	G. Hoogenboom
0900-1030	**Parallel Sessions: DSSAT and APSIM Groups** Conduct multi-year simulations for integrated assessment	
1030-1045	Tea/Coffee Break	
1045-1200	Participants create ACMO files from survey year and Multi-year simulations (ready for economists)	C. Porter
1200-1300	Lunch	
1300-1500	Participants collaborate to prepare summary graphs and short report for presentation by selected trainees	
1500-1600	**Plenary Session:** Participants present reports (10 min each) Trainers will critique and discuss results	
1600-1630	**Participant Feedback**: what worked, what is needed, follow up actions	
1630	**End Training**	

References

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen., J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W., Williams, J. R., and Wolf, J. (2013). Uncertainties in simulating wheat yields under climate change, *Nat. Clim. Change*, **3**, 827–832.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K. J., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A. R., Kersebaum, K. C., Kumar, N. S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M. V., Kim, S.-H., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., and Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors?, *Global Change Biol.*, **20**, 2301–2320.

Bationo, A., Tabo, R., Kihara, J., Hoogenboom, G., Traore, P. C. S., Boote, K. J., and Jones, J. W. (2012). "Building capacity for modeling in Africa", in Kihara, J., Fatondji, D., Jones, J. W., Hoogenboom, G., Tabo, R., and Bationo, A. (eds.), *Improving Soil Fertility Recommendations in Africa using the Decision Support System for Agrotechnology Transfers (DSSAT)*, Springer, Dordrecht, the Netherlands, pp. 1–7.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lisazo, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., and Tsuji, G. Y. (2010). *Decision Support System for Agrotechnology Transfer Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., and Jakas, M. C. (2006). Simulating soil C dynamics with EPIC: Model description and testing against long-term data, *Ecol. Model.*, **192**, 362–384.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., and Ritchie, J. T. (2003). The DSSAT cropping system model, *Eur. J. Agron.*, **18**, 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburne, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation, *Eur. J. Agron.*, **18**, 267–288.

Kersebaum, K. C., Boote, K. J., Jorgenson, J. S., Nendel, C., Bindi, M., Fruhauf, C., Gaiser, T., Hoogenboom, G., Kollas, C., Olesen, J. E., Rotter, R. P., Ruget, F., Thorburn, P., Trnka, M., and Wegehenkel, M. (2014). Analysis and classification of data sets for calibration and validation of agro-ecosystem models, *Environ. Model. Software*, submitted.

Penning de Vries, F. W. T., Jansen, D. M., ten Berge, H. F. M., and Bakema, A. (1989). *Simulation of ecophysiological processes of growth in several annual crops*, PUDOC, Wageningen, The Netherlands and International Rice Research Institute, Los Banos, p. 271.

Penning de Vries, F. W. T. and van Laar, H. H. (1982). *Simulation of plant growth and crop production*, PUDOC, Wageningen, the Netherlands.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria,

G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Agric. Forest Meteorol.*, **170**, 166–172.

Rosenzweig, C., Jones, J. W., Hatfield, J., Antle, J., Ruane, A. C., Boote, K., Thorburn, P., Validivia, R. O., Porter, C., Janssen, S., and Mutter, C. (2014). *Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.1*. Available at: http://www.agmip.org/regional-integrated-assessments-handbook. Accessed on 17 July 2014.

Stöckle, C. O., Donatelli, M., and Nelson, R. (2003). CropSyst, a cropping systems simulation model, *Eur. J. Agron.*, **18**, 289–307.

Ten Berge, H. F. M. (1993). "Building capacity for systems research at national agricultural research centers: SARP's experience", in *Systems approaches for agricultural development*, Penning de Vries, F. W. T., Teng, P., and Metselaar, K. (eds.), Kluwer Academic Publishers, Dordrecht, the Netherlands, pp. 515–538.

Tsuji, G. Y., Hoogenboom, G., and Thornton, P. K. (eds.) (1998). *Understanding options for agricultural production*, Kluwer Academic Publishers, Dordrecht, the Netherlands.

Williams, J. R., Jones, C. A., Kiniry, J. R., and Spanel, D. A. (1989). The EPIC crop growth model, *Trans. ASAE*, **32**(2), 497–511.

Conclusion

Major Findings and Future Activities

Cynthia Rosenzweig and Daniel Hillel

The Agricultural Model Intercomparison and Improvement Project (AgMIP) incorporates a number of major advances in the way that climate impacts, vulnerability, and adaptation are being simulated. At its core is a protocol approach that results in impact assessments being more scientifically credible and thus ultimately having greater value to the wide range of agricultural stakeholders. Moreover, the use of the protocol approach enables closer scrutiny and intercomparison of models and methods so that they can be improved over time. By creating a truly trans-disciplinary, systems-based approach, AgMIP impact assessments and evaluation of adaptations become useful to agricultural decision-makers at multiple scales. The chapters in this two-part set demonstrate the use of this approach and represent early steps towards the full realization of these new methods and their application.

Part 1, Section I. Overview of AgMIP

Major findings

AgMIP has developed new methods to assess climate change impacts on food security, income, and poverty for current farming systems and the types of farming systems that are likely to occur in the future. These provide more realistic projections of how climate change will facilitate or impede economic development. These new methods integrate climate, crop, livestock, and economic models to conduct multi-model climate change impact assessments that characterize differential impacts on smallholder groups even within a given region. Consideration of economics and adaptation gives a more complete picture of projected impacts of climate change on the agricultural sector. The new methods provide direct evaluation of yield, income, and poverty outcomes from pilot adaptation packages and development pathways.

At the global scale, crops in lower latitudes (where most developing countries are located) show greater vulnerability to climate change, and climate change will slow the pace of development in many current smallholder agricultural systems. In contrast to previous assessments that projected a period of increasing crop yields

before temperature effects reduced yields, AgMIP global gridded crop model results with realistic nitrogen fertilization show steadily decreasing yields for wheat, maize, and soybean in mid- and high-latitude regions even for small temperature increases; this finding is backed up by an independent analysis conducted for the IPCC of individual climate impact studies (IPCC, 2014).

Climate change is projected to exert upward pressure on global agricultural prices, but with large uncertainty (Nelson, 2014; von Lampe, 2014). Price uncertainty on the global market comes largely from economic models, with smaller contributions from crop and climate model uncertainty, although these can be substantial on the regional scale. Economic models differ primarily in assumptions about ease of land use conversion, intensification, and trade. The AgMIP global economic models include functions that economic systems utilize to respond to climate stresses, i.e., they respond to climate impacts by taking actions to reduce yield loss, increase crop area, and change demand.

Future activities

There is great potential to improve agricultural models and data to incorporate important features of current and possible future farming systems, including multiple crops, intercrops, livestock, and non-agricultural sources of income. Additional research investment is needed to improve the assessment of the key uncertainties in crop, biophysical, and economic dimensions of assessments.

Part 1, Section II. Methods of Regional Integrated Assessments

Major findings

AgMIP conducted the first set of comprehensive regional integrated assessments of climate change impacts on smallholder farmers in Sub-Saharan Africa and South Asia led by researchers from the regions themselves. The project developed new methods integrating climate, crop, livestock, and economic models to conduct climate change impact assessments that characterize impacts on smallholder groups. AgMIP projections of climate change impacts on agriculture are much more realistic than previous assessments because they take agricultural development into account. By using the best available data and multiple models, the assessments directly evaluated yield, income, and poverty outcomes, including the effects of adaptation packages and development pathways.

Future activities

AgMIP efforts for its next phase include improved representation of extreme events in the decision-support modeling framework; enhanced scope of regional integrated

assessments; and increased linkages to national and/or global scales. The next phase of work will also focus on the development of policies and adaptation packages in each region co-generated by AgMIP and its stakeholders, and assessments of policy and adaptation strategies to inform stakeholder decisions in each region. Furthermore, AgMIP will assess and report on stakeholder needs; document the methods resulting in capacity gains for project participants; and develop timely, accessible, and relevant communications.

Climate

Major findings

AgMIP climate datasets and scenarios allow protocol-based agricultural modeling activities across a wide range of disciplinary models, geographic regions, and temporal and spatial scales. These datasets and scenarios form a starting point for coordinated regional and global assessments in which consistency is important to assessment of international markets, comparative advantage, and the transfer of adaptation strategies. Within any given region or specific application, alternative climate datasets and scenario-generation methodologies may be available, and AgMIP incorporates these into its assessments as well.

Future activities

Over time, AgMIP will develop climate products and incorporate new approaches to enable global coverage for improved agricultural assessment. In future phases of AgMIP, focus will be on near-term climate change and extreme events, which stakeholders have labeled as high-priority topics for targeted research. Extreme events are often highly localized in space and extend observational networks, climate models, and scenario-generation methodologies to the limits of their functionality. Improved climate scenarios that capture the ways in which extreme conditions may be exacerbated by long-term climate changes will enable improved simulation of acute climate impacts and motivate land-use and policy-change decisions as new equilibria emerge.

Crop modeling

Major findings

Crop modeling is a critical part of integrated regional assessments in AgMIP. It needs to be undertaken with multiple crop models to characterize uncertainty in

predictions of production. To ensure comparability, it also needs to follow consistent protocols that specify methods for calibrating varieties, and application of crop models to simulate crop yields in farms under current climate and management, and under a range of climate change and adaptation scenarios. High-quality data are needed from experiments to calibrate the models. These experiments are designated AgMIP sentinel sites, and should include measurements of growth stages and yield, as well as information on soils, climate, and management. The calibrated crop models are then used to simulate crop production in farmers' fields to provide the primary yield input to the economic modeling. Information is needed on soils, management, and yields currently achieved in these fields.

The three major types of simulations done to date include yields under current management with current and future climates, yields under future cropping (or agricultural) systems arising from technology trends with current and future climates, and yields under future climate with adaptation (and/or greenhouse gas mitigation) strategies. Protocols have been defined to guide each of these steps, from what defines a sentinel site, to the information needed to interpret simulated yields and provide necessary data for economic models. The application of multiple crop models is supported by the AgMIP IT tools, which port shared information between different models and assist in the generation of management inputs for the farmers' fields, which can be too numerous (e.g., >100) to be done practically by hand.

The successful application of the crop modeling protocols and supporting tools is clearly demonstrated by the results from the AgMIP regional integrated assessments described in Part 2, Chapters 1–10 in this volume.

Future activities

The experience gained in developing and applying the AgMIP protocols have revealed some crop modeling challenges that need to be addressed in the future. One clear challenge for AgMIP is to move from analyzing cropping systems to agricultural systems, which often includes the integration of crops and livestock on farms. AgMIP protocols to date have focused primarily on crop modeling, yet most agricultural systems in the world are integrated crop–livestock systems that cannot be represented by crop modeling alone. Grasslands and livestock modeling need to be incorporated. AgMIP principles are being expanded to apply to both crops and livestock systems, i.e., "crop modeling" is becoming "agricultural-systems modeling". Information from local experiments (AgMIP sentinel sites) will be required to develop and test the grassland and livestock models in study regions, then these models will be deployed with regional farm data and inputs on management and climate. An example of the application of AgMIP crop modeling protocols to crop–livestock intensification in southern Africa is given in Part 2, Chapter 5 in this volume.

Another challenge is the further improvement of model interoperability, which is currently most operational in regard to soil–water dynamics and least operational in regard to soil carbon and nitrogen cycling. Ideally, parameters from one crop model can be uploaded into AgMIP databases and downloaded, reformatted, for use in another model. The greatest challenge is to increase the capacity of the crop models to represent a wider range of crop growth resource constraints (e.g., other nutrients in addition to nitrogen, ozone, pests, and diseases).

Representative agricultural pathways

Major findings

AgMIP has laid the conceptual foundations and developed new methods for designing representative agricultural pathways (RAPs) that can be coupled with global socio-economic pathways (e.g., SSPs). The use of RAPs are a key advance in agricultural model intercomparison and improvement, and for climate impact, adaptation and vulnerability assessment. AgMIP's goal is to design RAPs for all of the major agricultural regions of the globe. The first step in this process began with regional impact assessment teams created by AgMIP in collaboration with national and international institutions in Sub-Saharan Africa and South Asia (see Part 2, Chapters 1–10 in this volume).

Future activities

At the regional scale, RAPS will be improved by doing further research on key variables. Alternative RAPs will be developed, and extended to other regions. AgMIP teams will increase stakeholder participation and involve them early in the process.

The AgMIP economic team plans to revise the RAPs process methodology and tools, create a master list of indicators with detailed definitions that can facilitate the development of RAPs, and provide standard definitions of the indicators being used in the RAPs. AgMIP will also develop ways to archive and document the RAPs and related information so that they can be used by other researchers.

As regional teams create RAPs and implement integrated assessments at the regional and local scales, the next step is to scale them up to the national and global levels, thus leading to a consistent set of linked global and regional RAPs. These accomplishments will enable a new capability by the agricultural modeling community to carry out agricultural model intercomparison, and carry out impact, adaptation and vulnerability assessment consistently across scales. This capability will lead to the improvement of agricultural models and to a new generation of improved global and regional assessments.

Data interoperability tools

Major findings

The AgMIP harmonized data solution was developed in response to a need by the AgMIP community of researchers for interoperability of data inputs to multiple crop models in assessments of climate change on food security. The ACE harmonized data format provides a simple, flexible, and extensible means of handling site-based agricultural data from diverse sources and for making them available as input to multiple crop models. The key-value schema of the ACE harmonized data format provides an efficient and flexible means of defining and archiving the irregular site-specific data from diverse sources. The DOME provides a means for users to supply information such as management details, initial conditions, simulation time span, or hypothetical regimens, consistently and transparently to multiple models. Harmonization of simulated model outputs facilitates consistent analysis and interoperability of the results from multiple models and makes the data more readily available for input to economic models.

The AgMIP data-management system was designed to address the needs of a large, distributed, multi-model research community by adopting a rich, extensible vocabulary to describe site-based agricultural data from diverse sources. Flexible data structures allow both detailed and lesser quality records to be stored in an efficient database. Together, these provide a consistent set of assumptions and parameters that can be extrapolated to multiple models. For the first time ever, researchers and modelers are able to use these tools to run an ensemble of models on a single, harmonized dataset. This allows them to compare models, which leads ultimately to model improvements. Perhaps the most important outcome is that AgMIP has provided a platform that facilitates researcher collaboration from many organizations, across many countries. As AgMIP grows to include more regions, researchers, and modeling groups, the harmonized data format and translation tools will continue to be valuable resources.

Future activities

The current implementation of AgMIP data interoperability tools uses spreadsheet templates and desktop utilities to allow researchers to harmonize and translate site-based data. These tools filled an immediate need for the researchers but remain difficult to use. Next-generation tools will include more interactive user interfaces and web-based approaches. The existing data schemas and translators are sufficiently flexible to be implemented in next-generation utilities without redesign.

Part 1, Section III. Global Estimates of Climate Impacts on Agriculture

Coordinated Climate-Crop Modeling Project (*C3MP*)

Major findings

C3MP coordination has identified some general responses that warrant further explanation and interaction with the greater community of collaborators. Firstly, crop model calibrations may be achieved with respect to the optimal temperature for the specific crop/cultivar at a particular site. Secondly, C3MP is continuing assessments of the crop impacts response surfaces generated for each simulation. Thirdly, C3MP has also identified multiple simulations sets that are either co-located or are characterized by similar climates (i.e., similar temperature and rainfall), but display largely disparate mean yield values between different crop models. C3MP is actively working both to integrate the lessons learned in the updated protocols for Phase 2 of the project, and also to understand and share better these and other recent findings. Continuous interactions with the greater C3MP community will help to prioritize and organize these activities, and create new opportunities for study and evaluation.

Future activities

As the database of contributed sites continues to grow and improve in quality, C3MP has identified a set of analyses that can be performed at any location. These include, but are not limited to:

- *Analyses of current sensitivity*
  By examining the slope of the emulated response surfaces at the historical baseline climate's location ($\Delta T = 0°C$; $\Delta P = 0\%$; $[CO_2] = 360$ ppm), it is possible to examine the sensitivity of yield to each climate metric. Simulation sites where immediate sensitivity and potential for damages are high can be highlighted in regard to climate risks and vulnerability.
- *Climate change analyses* (*including CMIP5 GCMs*)
  Emulated impacts response surfaces also facilitate assessments of projected climate impacts on a given region and crop. By examining CMIP5 global climate model (GCM) outputs that correspond to simulation site locations, distributions of projected changes in growing season temperature and precipitation can be determined and coupled with $[CO_2]$ from the corresponding representative concentration pathway (Moss *et al.*, 2010) for any given time slice. These projections may then be used to calculate probabilistic yield-change estimates by using the emulated response surfaces. A similar approach is also possible with other climate model ensembles, in addition to data from various downscaling approaches or scenario-generation techniques.

- *Exploring uncertainties by using network of C3MP locations*
  C3MP will generate maps of crop modeling simulation locations that can be used to build the network of AgMIP sites and crop modelers around the world to facilitate comparison and collaboration in future studies. Such comparisons and crop response evaluations at multiple sites will also allow detailed investigations of model and crop response uncertainty, which may be characterized across models, geographic area, and other spaces.
- *Regional-based analyses*
  When representative simulation sites are contributed for a particular region (e.g., southeast South America), C3MP participants will undertake a more detailed investigation of that region. Such regional analyses include comparisons of simulation set coverage relative to major agricultural regions, assessments examining the relative impacts of climate change on different subregions, and evaluations of the implications of updated climate scenarios or downscaled datasets on the region.
- *Crop-based analyses*
  Similarly, when simulation sites are representative of a particular crop (e.g., sorghum), C3MP participants will undertake a more detailed investigation of C3MP results for particular crop. Possible areas of investigation include global coverage of the crop model simulations relative to the crop's major growing regions, evaluation of crop models comparing model similarities and differences, and interactions between crop responses and other environmental factors. The global community of modelers for each crop is highly encouraged to undertake and lead these assessments. Discussion may be easily facilitated via the C3MP research website and forums.
- *Crop model-based analyses*
  When representative simulated sites are contributed for a particular crop model (e.g., APSIM, DSSAT, STICS), C3MP participants will undertake a more detailed investigation of C3MP results for that crop model. Potential areas of study include lessons learned about the sensitivity of the crop model to key climate change factors. Furthermore, efforts are underway by AgGRID to execute the C3MP sensitivity tests for various global gridded crop models. Though direct comparisons with the C3MP results submitted from point-based crop models are challenging, the consistency between these and the global gridded model C3MP results can provide insight into regional and global crop responses changes in carbon, temperature, and precipitation. A large network of C3MP point-based simulations can also aid AgGRID development, by providing a means for evaluating their spatial performance.

C3MP will continue to welcome more participants, accept additional results from existing or new members, vet and evaluate the existing contributions, refine the emulator approach for various sites, and expand participation among additional

crop modeling teams, and encourage coverage by modelers of under-represented countries and regions. C3MP will work to identify opportunities for collaboration among participants and coordinate publications and studies that are unique. Registration is and will remain open at www.agmip.org/c3mp. Interested parties may contact c3mp@agmip.org at any time for further information on how to contribute to this unique and rigorous global research effort.

Part 1, Section IV. Building AgMIP Science

Uncertainty in agricultural impact assessment

Major findings

The overall objective of uncertainty analysis in climate change impact assessment is to define and apply methods for qualifying realistically the end-to-end uncertainty and for apportioning that uncertainty to specific causes. One major issue is the current state of total uncertainty quantification for impact assessment. This should not be thought of as a single result, since uncertainty depends on context. Whether related to farm scale or regional scale, or whether detailed data for calibration are available or not, etc. Detailed information is available about uncertainty in climate projections and also about uncertainty in crop model predictions/projections, and AgMIP is providing information about uncertainty from impact studies that involve multiple climate models providing input to multiple crop models. On the other hand, there seems to be much less information available about uncertainty in the estimation of the economic impact of climate change at regional scales. The question then is how to combine the available information into estimates of the total uncertainty of impacts assessments. This also helps to identify future research needs for improving the estimation of total uncertainty.

Future activities

Methodological areas for future research on improving uncertainty estimation in agricultural climate change impact assessment concern the use of multi-crop model ensembles, since this is a recent development that will have a large impact on uncertainty estimation. Key research topics and questions include:

- How does the quality of the uncertainty estimate vary with the choice of crop models in the ensemble and the number of crop models? What can one say about how to choose crop models for the ensemble?
- In climate modeling, one creates super-ensembles by taking multiple climate models and, for each climate model, multiple parameterizations or multiple initial conditions. Would the use of such super-ensembles improve the estimates of uncertainty for crop, livestock, or economic models?

- Information about errors in hindcasts exists for each crop model. Should one take that into account in estimating uncertainty using multiple crop model ensembles? In which circumstances is this important? How should it be done?
- How good are estimates of uncertainty and how is this determined?
- Using the average or median of crop model projections often gives good agreement with observations. What is the uncertainty of those ensemble predictors?
- In crop modeling, uncertainty assessment does not always lead to model improvement. How can the specific aspects of models that account for uncertainty be identified?
- How can uncertainty in regional economic models be estimated?
- How does climate uncertainty propagate downstream into crop and economic modeling components of integrated assessment?
- How can model and parameter subsets be determined that will make the best use of limited resources for multi-disciplinary, multi-model integrated assessment?
- How can the uncertainty due to factors not taken into account, such as pests and diseases, be estimated?

Scaling-up crop models for large-area climate change impact assessments

Major findings

Differences in regional averages of simulated potential yields based on model ensemble means were small, depending on the number of sampling points considered. Average yields tend to decline as the size of the grid cells increases until a size of 50×50 km^2. The higher average yield at the large grid cell size of 100×100 km^2 may be caused by the methodology of considering border grid cells, which results in a larger total area of this cell size as compared to smaller grid cell sizes. Variability in simulated potential yield through space increases with increasing number of sample points and decreasing grid cell size. If information on the spatial variability of yields is required, studies based on few sample points or large grid cells may be insufficient. This applies particularly to areas where spatial variability in environmental conditions is high.

Future activities

Future research on better understanding the effects of scaling-up crop models for large-area assessments should focus on:

- Considering spatial variability in soils.
- Assessing the role of spatial variability in management, particularly for N-fertilization, sowing dates, and varieties grown. A particular challenge is to understand the impact of methods to scale-up crop rotations (Teixeira *et al.*, 2014).

- Generalizing of results across crops and regions.
- Evaluating model structure and parameters.
- Determining why ensemble means replicate observations better than individual models.

As these and other results suggest that uncertainty from crop models and GCMs are larger than from scaling methods (with the qualification that soil and management variability has not been considered), future research should also focus on improving crop models for large-scale application. Here the question of appropriate model detail becomes important (Adam *et al.*, 2011). To date, large-area crop models have not been systematically developed to capture the relationships important at an aggregated regional scale. The same issue applies to long time horizons.

At large spatial and long temporal scales, crop physiological processes as considered in crop models may be less important, particularly in regions like Africa with a large share of low-intensity farming systems (Webber *et al.*, 2014). Hence a new generation of crop models may be needed that adequately considers the range of factors, processes, and relationships relevant at larger scales. Such a new generation of crop models may be more suited to provide relevant inputs to the integrated assessment modeling (IAM) that is used to explore multi-sector outcomes and policies related to climate change (Ewert *et al.*, 2014).

Statistical analysis of simulated yield datasets

Major findings

Yield data simulated by an ensemble of complex dynamic-process crop models can be summarized by statistical meta-models based on random coefficient regressions. These statistical models describe the between-crop-model variability of the simulated yield data using probability distributions. They can be used to compute key quantities such as mean yield loss, percentiles of yield loss, and probabilities of yield loss as functions of temperature change and CO_2 concentration change. These meta-models can thus be helpful for analyzing the risk of yield loss due to climate change at the locations where the original simulations were conducted. Analysis of two yield datasets generated by the AgMIP model intercomparison studies for maize and wheat showed that:

- Thresholds of temperature increase and CO_2 concentrations leading to a specific risk level of maize and wheat-yield loss can be computed with the meta-model.
- Divergence among the maize and wheat crop models and therefore uncertainty in the simulated results increases as a function of temperature (the higher the temperature change, the higher the between-crop-model variability).

- High CO_2 concentrations are likely to outweigh the negative effect of increasing temperature, which leads to yield gains for wheat, but not for maize with climate change.

Future activities

Meta-model analyses could be extended in several ways. They could be applied to a dataset including simulations obtained for a higher number of sites. It will be then possible to include co-variables describing site characteristics (e.g., soil type, agricultural practices) in the meta-model in order to explain the origin of the between-site variability. The meta-model could be extended in order to describe the between-year variability of yields and to analyze the risk of extreme yield values for different climate scenarios. This could be achieved by including one or several additional random effects in the meta-model and by fitting this model to yearly yield data.

Part 2, Section I. Sub-Saharan Africa

Major findings

Agriculture in Sub-Saharan Africa (SSA) is already experiencing climate change-related effects that call for regional integrated assessments, yet capacity for these assessments has been low (see Part 2, Chapter 1 in this volume). AgMIP is advancing research on integrated regional assessments of climate change involving climate, crop, and economic modeling and analysis. Through AgMIP, regional integrated assessments are increasingly gaining momentum in SSA, and multi-institutional RRTs centered in Eastern, Western, and Southern Africa are generating new information on climate change impacts and adaptation in selected agricultural systems (see Part 2, Chapters 2–5 in this volume). Key findings include:

- Even with agricultural development, climate change generally will exert negative pressure on maize yields of vulnerable smallholder farmers in SSA, across the four different regions and systems assessed.
- Without adaptation, climate change leads to increased poverty in some locations in SSA compared to a future in which climate change does not occur.
- Adaptation can improve smallholder farmer responses to climate change in SSA.
- However, many farmers lacked the capability to respond effectively to the increasing climate risks projected for their regions.
- Of the four regions assessed, AgMIP expert teams identified improved varieties, sowing practices, fertilizer application, and irrigation applications as prioritized adaptations. These targeted adaptation packages were able to overcome a portion of detrimental impacts but could not compensate completely in many locations.

Future activities

AgMIP's need for good data to conduct integrated modeling within Sub-Saharan Africa is spurring the setting up of new experiments to generate more high-quality datasets. Further investment in research and development is needed to develop recommendations for the different production systems and environments, and increase capacity building at the national level. The stakeholder-involvement process is a key component and in the next phase, AgMIP will engage more with stakeholders for this knowledge to reach a wider group of users. Current research is helping identify most vulnerable farmers so that policymakers can make plans to help them minimize climate-related risks.

Part 2, Section II. South Asia

Major findings

Understanding the response of current agricultural production to climate variability and future climate change is of utmost importance to secure food and livelihoods for South Asia's growing population. AgMIP South Asian regional research teams undertook climate–crop–economic integrated assessments of food security for districts in these countries, with the goal of characterizing the state of food security and poverty across the region, and projecting how these are subject to change under future climate conditions (see Part 2, Chapters 7–10 in this volume). Key findings include:

- Even with agricultural development, climate change generally will exert negative pressure on rice yields of smallholder farmers in South Asia.
- Without adaptation, climate change leads to increased poverty in many locations in South Asia compared to a future in which climate change does not occur.
- Adaptation can significantly improve smallholder farmer responses to climate change in South Asia for all but the smallest farm sizes.
- Farmers lacked the capability to respond effectively to the increasing climate risks projected for their regions.
- Of the four regions assessed, AgMIP expert teams identified improved varieties, sowing practices, fertilizer application, and irrigation applications as prioritized adaptations. These targeted adaptation packages were able to overcome a portion of detrimental impacts but could not compensate completely in many locations.

Future activities

Agricultural production across South Asia is subject to much variability, due to both natural climate fluctuations and socio-economic policies and global shocks,

and is also potentially at risk under future climate change conditions. AgMIP will continue to mobilize inter-disciplinary scientists across South Asia to participate in a coordinated investigation of the impact of climate change on food security and to help scientists from highly varied and disparate subregions across South Asia, representing Bangladesh, India, Nepal, Pakistan, and Sri Lanka convene, learn new methodologies, and engage with their decision-making communities in the process of undertaking integrated assessments.

Part 2, Section III. Other AgMIP Regions

Brazil

AgMIP methods for regional integrated assessments is already helping to identify areas of high climatic risk in Brazil for the next 20 years and to estimate the future productivity of the main Brazilian crops. Advanced studies of extreme events show the need for Brazil to quickly search for adaptation options for agriculture, which plays a significant role in the national economy. Taken together, AgMIP has great potential to contribute to science-based public policies linked to portending climate change in the country.

China

Climate change has had measurable impacts on agriculture in China in the past decades, and is projected to have a major impact on agriculture in future. However, these impacts can vary significantly across regions within China. Although climate impact studies have progressed in recent years, there is still a long way to go. Next steps should focus on adaptation to climate change. New integrated agricultural system models that account adequately for adaptations should be developed, and cross-sector integrated assessments should be conducted to design effective adaptation strategies.

Part 2, Section IV. Capacity Building and Outreach

AgMIP training program: multiple models and tools

Major findings

The AgMIP Multiple Model Course trained crop modelers on two different crop models, allowing regional project teams to meet regional integrated assessment goals. The experience provided ways improve future multiple-model training courses. Such training is clearly needed and valued by the crop modeling

participants. The course generally went smoothly where the number of students was small (10–12) and the crops modeled were fewer. Future courses with multi-model agendas will need to ensure better beginning training or vetting of the participants. The use of trainers and AgMIP resource persons was very valuable, as they assisted with the many small working groups that exceeded the number of instructors available.

Future activities

The need for continued training in crop modeling is highlighted. Distance training modules can be designed, but will require coordination with DSSAT and APSIM modeler groups who have the training materials. The use of the IT tools for multi-model use and translation of data formats from one model to the other could be set up as a distance-training module within AgMIP. Another approach is to encourage the new "train-the-trainers" to lead crop model training courses in their own regions and institutions.

In Summation

This two-part set — the *Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assesments* — has been the first to be entirely devoted to AgMIP (www.agmip.org). AgMIP is a major international research program focused on improving agricultural systems models for use in assessment of climate change and agriculture. The goal of the two parts has been to advance the field by providing detailed information on new simulation techniques and assessment being conducted by this program. It has presented information about new methods of global and regional integrated assessment, result from agricultural regions around the world, and adaptation strategies for maintaining food security under changing climate conditions. AgMIP is bringing agricultural modelers and modeling groups together to compare and thus improve their models. This interaction is helping to develop a better understanding of systems approaches across the agricultural modeling community. These are now being used to conduct coordinated global and regional assessments for decision-makers around the world so that food security may be sustained under climate change conditions.

References

Adam, M., Van Bussel, L. G. J., Leffelaar, P. A., Van Keulen, H., and Ewert, F. (2011). Effects of modelling detail on simulated potential crop yields under a wide range of climatic conditions, *Ecol. Model.*, **222**, 131–143.

Ewert, F., Rötter, R. P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K. C., Olesen, J., van Ittersum, M. K., Janssen, S., Rivington, M., Semenov, M. A., Wallach, D., Porter, J. R., Stewart, D., Verhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P. P., Bartošová, L., and Asseng, S. (2014). Crop modelling for integrated assessment of climate change risk to food production, *Environ. Model. Software*, submitted.

Intergovernmental Panel on Climate Change (IPCC) (2014). "Climate Change 2014: Impacts, Adaptation and Vulnerability", *IPCC Working Group II contributions to AR5*.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment, *Nature*, **463**(7282), 747–756.

Nelson, G. C., van der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., von Lampe, M., d'Croz, D. M., van Meijl, H., Müller, C., Reilly, J., Robertson, R., Sands, R. D., Schmitz, C., Tabeau, A., Takahashi, K., Valin, H., and Willenbockel, D. (2014). Agriculture and climate change in global scenarios: why don't the models agree, *Agricultural Economics*, **45**(1), 85–101.

Teixeira, E. I., Brown, H. E., Sharp, J. M., Meenken, E. D., and Ewert, F. (2014). Evaluating methods to simulate crop rotations for regional climate change assessments — a case study on the Canterbury plains of New Zealand, *Environ. Model. Software*, in review.

von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., d'Croz, D. M., Nelson, G. C., Sands, R. D., Schmitz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., and van Meijl, H. (2014). Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison, *Agricultural Economics*, **45**(1), 3–20.

Webber H., Gaiser T., and Ewert F. (2014). What role can crop models play in supporting climate change adaptation decisions to enhance food security in Sub-Saharan Africa?, *Agric. Syst*., **127**,161–177.

Appendix 1

This page intentionally left blank

AgMIP

The Agricultural Model Intercomparison and Improvement Project

MULTIPLE CROP MODEL TRAINING PROGRAM

MARCH 25-29 2013
ICRISAT, INDIA

Report on AgMIP Multiple Crop Model Training Program 25-29th March, 2013 ICRISAT, India

Table of Contents

Introduction....2
Goals and Objectives....2
Pre-workshop Activities....3
Opening remarks and expectations....4
Day 1: Overview of DSSAT and APSIM crop models....4
Day 2: Overview: consideration of soils and management; parallel DSSAT and APSIM sessions; exploration of soil, weather, management, and crop data; understanding model-specific genetic coefficients; feedback on progress and issues....4
Day 3: AgMIP Protocols and Integrated Assessments....5
Day 4: AgMIP integrated assessments; analyzing farm production; using AgMIP tools to handle missing data; verify inputs and simulate productivity....5
Day 5: Seasonal analyses; multiyear simulations, ACMO files, collaborative preparation of reports....6
Appendix I: AgMIP SA and SSA participants identified issues relevant across the different project teams....7
Opportunities for training....8
Suggested further capacity building (Team wise)....8
Appendix II. Workshop agenda and detailed program....9
Appendix III. Participants for the first AgMIP South Asia workshop on integrated regional coordination in ICRISAT, India, 25-29th March 2013....14

Acknowledgements

This workshop was possible owing to strategic collaboration for the advancement of proficiency in multiple crop modeling methods as envisaged among the AgMIP Principal Investigators, Drs. C. Rosenzweig, NASA/Goddard Institute for Space Study; J. Jones, University of Florida (UF); J. Hatfield, USDA Agricultural Research Service (ARS) and Dr. P. Craufurd, Program Director for Resilient Drylands Research at the International Crop Research Institute for the Semi Arid Tropics (ICRISAT). The workshop was planned and executed with leadership contributions from Drs. K Boote, UF; G. Hoogenboom, Washington State University (WSU); J. Jones , UF; J. Hargreaves, AU Commonwealth Scientific and Industrial Research Organization (CSIRO); and C. Porter, UF. Contributions were provided also by Drs. D. Guntuku, ICRISAT and, C. Mutter, Columbia University. Direct support from ICRISAT was enabled by funding from the research program on Climate Change Agriculture and Food Security. Support of participating Sub-Saharan Africa and South Asia crop modelers was enabled with funding from the UK Department for International Development, in partnership with USDA/ARS. In-kind support was provided by ICRISAT, CSIRO, WSU, and UF. This workshop report was prepared by D. Guntuku, P. Rao, and V. Sumanth (all at ICRISAT) and other members of the AgMIP South Asia Regional Coordination Team with additional inputs from D. Murthy, K. Boote, C. Mutter and S. Lifson.

Introduction

The Agricultural Model Intercomparison and Improvement Project (AgMIP) is a major international effort linking the climate, crop, and economic modeling communities with cutting-edge information technology to produce improved crop and economic models and the next generation of climate impact projections for the agricultural sector. AgMIP aims to utilize inter-comparisons of various types of methods to improve crop and economic models and ensemble projections. It also looks to produce enhanced assessments by the crop and economic modeling communities researching climate change impacts on agriculture and adaptation to these impacts. Capacity building is one of the major aspects of AgMIP. To enhance the capacities of the crop modelers in various teams, the AgMIP Multiple Crop Model Training was planned with the objective of providing training on the use of multiple crop models for AgMIP Regional Integrated Assessments. The training program mainly aimed at conducting parallel sessions on DSSAT and APSIM as well as sessions on AgMIP IT tools that facilitate the use of multiple crop models for simulating crop production variations associated with farm survey data. Participants focused on learning one model (either DSSAT or APSIM), and brought results from another model for comparison.

Goals and Objectives

The AgMIP Multiple Crop Model Training Program was organized to assist the South India, Sri Lanka and Sub-Saharan Africa (SSA) teams in the use of multiple crop models for AgMIP Regional Integrated Assessments. The main objectives of this training were to

1. Provide training on Multiple Crop Model Training for each AgMIP regional integrated assessment, mainly focused on APSIM and DSSAT;

2. Review the fast track results and provide suggestions for improvement.

Summary and Impressions of Multiple Crop Modeling Course - ICRISAT

K. J. Boote, C. H. Porter, G. Hoogenboom, and J. Hargreaves

1. The course was clearly needed and valued by the crop modeling participants. It was needed, because some had not truly completed the Fast Track at this point. They worked very hard during the 1-week courses, even after hours.
2. Generally, the courses went smoothly, especially in Nepal as there were smaller numbers for us to handle. The Pakistani team was ready, having completed a thorough report. The Nepalese participants were excellent.
3. The 40 or so participants at ICRISAT center were eager to learn and fairly skilled in their abilities, but the diverse number of crops and regions made this workshop more difficult for us to handle. In addition, there were a number of participants who really needed a beginning crop modeling course, and they struggled.
4. The use of trainers and resource persons was very valuable and worked well, as they assisted small working groups as the four principal instructors could not be everywhere.
5. On Tuesday morning we asked for reports on the Fast Track during both workshops. This was highly valuable, as we discovered a number of problems and issues. Gerrit and Ken had short sessions with each team that used DSSAT for Fast Track,

checking their model input files, set-ups, and initial conditions. We discovered a number of problems such as not setting initial conditions for soil water, crop residue, nitrate and ammonium, and failure to handle rice as paddy. Some teams micro-calibrated to each farmer field in some respects (which was discouraged). Others did the climate scenarios incorrectly. These issues will require re-doing their simulated Fast Track. Many of these problems would not have been evident in the submitted report (that we later evaluated).

6. The IT Tools were successfully used for entry and conversion of survey data to DSSAT files for maize and millet (and during the course to wheat). Conversion to DSSAT CERES-rice did not work as well because the Tools had not previously been used for paddy rice. The tools to convert to APSIM-ready files worked only for maize and failed for all other crops. Manual manipulation (7 hours of work by Subash) got files to run for APSIM wheat. Some teams did not use the IT Tools at all, but did all the work within DSSAT. Even teams that planned on APSIM as Fast Track model, did simulations with DSSAT first, because of the tools. Conclusion is that IT Tool translation tools to APSIM need improvement.
7. No one successfully parameterized soil C modules, either SOM3 or fraction inert soil C for DSSAT and APSIM, respectively. CENTURY SOC was generally not used (never used for Rice), although we need to survey exact numbers on this.
8. Most teams had evolved to one or two point persons doing the crop modeling. The persons starting with strong background in one model benefited most from learning about a new model, but the majority of other participants probably did not get enough basic training in the "new" model to become effective users. They will still need more basic training in that model. So, multiple model training was important to achieve project objectives (use of multiple models for same genetic calibration and survey region), but was not sufficient for true training in that second model.
9. The Regional Teams need advice on what simulations are needed by the time of July Regional Workshops beyond the first Fast Track report (what additional models, additional farm survey regions). They need advice on publications that are anticipated to produce.
10. We discussed the roles of resource persons. Some resource persons need to be encouraged to become more involved.
11. We need a WebEx meeting with the resource persons on how to use the IT Tools. That needs to include some crop modelers (Ken, Gerrit, Jim) to indicate what is expected of the crop model inputs and next steps.

Pre-workshop Activities

The South Asia (SA) coordination team did the following pre-workshop activities:

- The South India, Sri Lanka and Sub-Saharan Africa teams were informed to prepare on various requirements such as survey data, fast track outputs, and climate data so that they could review the datasets during the training program. To this effect attached is the letter sent to all the participants;

AgMIP MCMT PREPARATIONS-COMPUTER,DATA,MODEL Requirements.pdf.pdf

- Initiate activities to accomplish what is needed for the SA-wide Multiple Crop Model Training Program;
- Develop an inventory of available Data for Calibrating Genetic Coefficients and Data for farm survey yields that are needed for training;
- Select regions, study sites, and teams that are to be targeted, and prepare a summary of each to discuss in the training.

Opening remarks and expectations

Dr. Dileepkumar Guntuku, PI for the South Asia Regional Coordination Team, welcomed the delegates and participants from South Asia, Sub-Saharan Africa, AgMIP Leadership team members, and other AgMIP members and asked to include multiple models, scenarios, locations, scales, crops, and participants to explore uncertainty and the impact of data quality and methodological choices. He requested to collaborate with regional experts in agronomy, economics, and climate to build a strong basis for applied simulations addressing key climate-related questions.

Dr. Peter Craufurd welcomed all and thanked the leaders, trainers and participants of AgMIP for their interest and hard work. Dr. Ken Boote, from the University of Florida, gave an overview on the AgMIP Multiple Crop Model Training Program, its various activities and also briefed about the plan for the 5-day training program.

Day 1: Overview of DSSAT and APSIM crop models

Dr. Ken Boote explained the course objectives and gave an overview of the program. In his presentation he highlighted the importance of Model Improvement and Intercomparison, and Climate Change Multi-Model Assessment. He clearly stated that it is not a beginner's crop modeling course and that the main emphasis would be on the use of crop models to account for yield variability attributed to farm management, soils, and long-term weather. He explained that the results will be used by economists. Later, he presented an Overview of DSSAT growth and phenology.

Dr. John Hargreaves presented an overview of APSIM crop growth and phenology where he covered various aspects of phenological development, leaf development, biomass production, leaf senescence, and root development.

Later, Dr. Boote discussed the principles of genetic coefficient calibration. He explained various ways to determine genetic coefficients and of estimating cultivar coefficients using field data.

Day 2: Overview: consideration of soils and management; parallel DSSAT and APSIM sessions; exploration of soil, weather, management, and crop data; understanding model-specific genetic coefficients; feedback on progress and issues

Day 2 started with Dr. Gerrit Hoogenboom's presentation: Initializing Soils and Management for Reliable Simulations. He insisted in providing accurate soil and crop coefficient inputs for better simulations. He also highlighted the importance of initial conditions and cropping history of the fields which are critical inputs for crop models.

Each participating team (i.e. South India, Southern Africa, Eastern Africa, Sri Lanka, Indo-Gangetic Basin, and CIWARA) presented their fast track results. Then participants broke out into two groups (APSIM and DSSAT) for parallel sessions. In these parallel sessions, teams worked with the collected data for calibration of genetic coefficients and had hands-on exercises in learning procedures for inputting new crop, soil, management, and weather data for their new crop model; and entering new experiments for use in estimating GCs for their new crop model. The trainers in DSSAT and APSIM helped the participants in the exercises.

During Day 2, Ken Boote and Gerrit Hoogenboom met individually with each team to specifically look at model files created by each team, to ensure proper file creation so that crop models correctly considered crop inputs such as fertilizer N, irrigation or paddy, crop residue, and soil organic C pools. They evaluated team methods for setting genetic coefficients for their selected cultivars, as well as simulating farm survey yields.

Day 3: AgMIP Protocols and Integrated Assessments

The teams were satisfied with the idea of parallel sessions as these provided a lot of insight, as well as answers to issues within and across the teams. Ken Boote and Cheryl Porter gave presentations on the Goals of AgMIP Integrated Assessments: creating economic inputs and results for DSS and AgMIP tools and procedures for integrated assessment. Ken Boote explained in detail the steps associated with integrated assessments. He described the AgMIP tools and procedures for using farm household survey data to create input files that are formatted for use in different crop models. He also described the crop model output files that are needed for input to the economic models for integrated climate assessments.

Cheryl Porter explained the IT Tools used for creating model-ready files using DOME, QuadUI, and ACE-ACMO-DOME Desktop utilities. She also talked about the types of Simulations for Integrated Assessments and the steps to survey data simulations. Finally, she informed of the changes in IT Tools since the regional workshops.

In the afternoon, AgMIP leadership members reviewed the fast track results of each team and clarified issues related to model calibration and the Matched Data Approach in simulating survey data.

Day 4: AgMIP integrated assessments; analyzing farm production; using AgMIP tools to handle missing data; verify inputs and simulate productivity

Day 4 started with a plenary session by Ken Boote, with the presentation Methods for Analyzing Farm Survey Observed and Simulated Production.

In his presentation, Dr. Boote explained in detail the steps involved in integrated assessment. He explained the distinction between matched observed and simulated data and unmatched data. He also highlighted that the Data Overlay for Multimodal Export (DOME) is a file type that is used by AgMIP tools to provide additional data needed for the crop models, but which is missing from the field survey data. Further in his presentation, he also explained the Guidelines for Analysis of Crop Model Simulated Outputs for Matched Fields and bias correction.

Participants worked in break out groups and parallel sessions continued. They also had hands-on exercises on the use of AgMIP IT tools using their respective team's farm survey data.

Day 5: Seasonal analyses; multiyear simulations, ACMO files, collaborative preparation of reports

Dr. Hoogenboom gave a presentation on Seasonal Analyses with Multiple Weather Years, Evaluating Uncertainty and Risk Using Models. The parallel sessions continued and teams worked with their survey data to conduct multiple year simulations using IT tools with two crop models (DSSAT/APSIM). After successful calibration of the models, each team ran the two models with survey data using AgMIP IT tools. Finally, each team presented their brief report on their model outputs for each climate change scenario.

Appendix I: AgMIP SA and SSA participants identified issues relevant across the different project teams.

1. Team-wise fast track analysis data was reviewed by AgMIP leadership.
2. The concept of MCM training worked well as the majority of the participants expressed their satisfaction over the structure of the training program.
3. The concept of trainers training trainees was very effective and needs to be replicated by the respective teams by conducting boot camps based on specific needs.
4. Availability and access to data, especially climate data (temperature and radiation), and farm survey data is needed for economic models.
5. Reliance on existing datasets: cannot conduct new experiments to acquire data as required for calibration and validation. Accessing already available datasets such as crop yields and genetic co-efficient is a big challenge because most of the teams are having issues with the data.
6. Development and Training on new AgMIP tools, especially for rice crop, is the topmost priority (DOME for Rice is needed that incorporates puddling aspects)
7. Sri Lanka team required further training on DSSAT model and required to obtain good data sets for calibration of sugarcane crop.
8. South India (AP) & Sri Lanka teams need refresher on TOA-MD Model and Climate analysis.

Opportunities for training

As the members in the different teams had hands-on exercises in different crop models, they can plan to replicate these trainings to build capacity within the team and beyond:

Target groups	Mode
Graduate Students	Creating interest and awareness on climate analysis and crop modeling, either by providing training or including topics in their curriculum.
Senior Research Fellow and Fellow Scientists	Providing hands-on training regularly to build the team on crop modeling/climate.
Policy makers	Keep informed about the outcomes by short training/meeting through status reports, fact sheets.

Suggested further capacity building (Team wise)

Sri Lanka	South India	IGB	Pakistan & SSA
DSSAT and Climate modeling	Climate modeling and Infocrop	Climate modeling and Infocrop	Climate modeling

Appendix II. Workshop agenda and detailed program

AgMIP Multiple Crop Model Training Program

25-29 March 2013

ICRISAT
Andhra Pradesh, India

Program

Day/Date/Time	Session		Facilitator
Day 1 Monday 25 March		**Overview:** Overview of DSSAT and APSIM crop models, specifically how phenological development, growth and yield, and soil water dynamics are modeled, and overview of the genetic coefficients needed for each model.	
0800-0830		Registration	
0830-0900		**Plenary Session** - Welcome	G Dileepkumar
		Introductions – each participant	All
		About AgMIP Project	Peter Craufurd
0900-0940		Course objectives, overview of program	Ken Boote
		A broad overview and discussing APSIM, DSSAT including AgMIP Integrated Assessment perspective	
0940-1000		Group Photo, Tea/Coffee break	
1000-1100		Overview of DSSAT growth and phenology	Ken Boote
1100-1200		Overview of APSIM growth and phenology	John Hargreaves
1200-1300	Lunch		
1300-1400		Principles of genetic coefficient calibration	Ken Boote
1400-1430		Discussion – Issues with data and calibration	Instructors
1430-1445		Tea/Coffee Break	

1445-1700	**Parallel Sessions: DSSAT and APSIM Groups** Model installation and operation Example calibration of genetic coefficients Procedures for inputting new crop, soil, management, weather data. Entering new experiments for use in estimating GCs	
1700-1730	**Plenary Session**: Discussion of progress, issues	Instructors
1830	Welcome Dinner	
2030-2130	**Optional Session** for review and refinement of data, prior calibrations, methods	
Day 2 Tuesday 26 March	**Overview:** Consideration of soils and management; parallel DSSAT and APSIM sessions; exploration of soil, weather, management, and crop data; understanding model-specific genetic coefficients; feedback on progress and issues; optional evening session for review and practice.	
0830-0930	**Plenary Session:** Initializing soils and management for reliable simulations	G. Hoogenboom
0930-1200	**Parallel Sessions: DSSAT and APSIM Groups** Work with participant's data (use AgMIP IT tools as available to convert files); review their prior simulations. Soil Weather Management Crop observations Verifying inputs and simulations	
1200-1300	Lunch	
1300-1700	**Continue Parallel Sessions: DSSAT and APSIM Groups** Model-specific genetic coefficient lectures Calibrate model for genetic coefficients	
1700-1730	**Plenary Session:** Discussion of progress and issues	
1930-2100	**Optional Session** for review, work, and practice	

Day 3 Wednesday 27 March	**Overview:** Continue parallel sessions, undertaking genetic coefficient calibrations; present findings in plenary; utilize AgMIP tools and procedures for integrated assessment; initiate field survey data analysis; optional evening session for review, work and practice.	
0830-1200	**Parallel Sessions: DSSAT and APSIM Groups** Participants complete estimation of genetic coefficients Prepare summary graphs, report	
1200-1300	Lunch	
1300-1400	**Plenary Session:** Presentation of genetic coefficient calibrations (5 minutes each)	
1400-1445	Discussion of calibrations, feedback, recommendations to teams for follow-up	Instructors
1445-1500	Tea/Coffee Break	
1500-1530	**Plenary Session:** Goals of AgMIP integrated assessment (creating economic inputs & results for DSS)	Ken Boote
1530-1630	AgMIP tools and procedures for integrated assessment Use AgMIP Tools to complete entry of field survey data Create Overlay for "missing" initialization/management Convert field survey data into model-ready forms	Cheryl Porter
1630-1700	**Individual Study in Plenary:** Participants working on their field survey data	
1700-1730	Discussion	
1930-2100	**Optional Session** for review, work, and practice	

Day 4 Thursday 28 March	**Objectives:** AgMIP integrated assessments; analyzing farm production; using AgMIP tools to handle missing data; verify inputs and simulate productivity; analyze, bias correct, interpret, question reliability/believability of findings.	
0830-0900	**Plenary Session:** Methods for analyzing farm survey observed and simulated production	Ken Boote
0900-0915	Discussion	
0915-0930	Tea/Coffee Break	
0930-1200	**Parallel Sessions: DSSAT and APSIM Groups** Verify inputs (management, soils, IC, cultivar) & simulate Analyze simulated results, mean, cumulative probability Compute bias and determine if adjustments are needed Are results reliable? Believable?	
1200-1300	Lunch	
1300-1700	**Parallel Sessions: DSSAT and APSIM Groups** Verify inputs (management, soils, IC, cultivar) & simulate Analyze simulated results, mean, cumulative probability Compute bias and determine if adjustments are needed Are results reliable? Believable?	
1700-1800	**Plenary Session:** Discussion of problems and issues	

Day 5 Friday 29 March	**Objectives:** Seasonal analyses; multi year simulations, ACMO files, collaborative preparation of reports (for presentation by selected trainees); presentation; feedback on training.	
0830-0900	**Plenary Session:** Seasonal analyses with multiple weather years	G. Hoogenboom
0900-1030	**Parallel Sessions: DSSAT and APSIM Groups** Conduct multi-year simulations for integrated assessment	
1030-1045	Tea/Coffee Break	

1045-1200	Participants create ACMO files from survey year and Multi-year simulations (ready for economists)	C. Porter
1200-1300	Lunch	
1300-1500	Participants collaborate to prepare summary graphs and short report for presentation by selected trainees	
1500-1600	**Plenary Session:** Participants present reports (10 min each) Trainers will critique and discuss results	
1600-1630	**Participant Feedback**: what worked, what is needed, follow up actions	
1630	**End Training**	

Appendix III. Participants for the first AgMIP South Asia workshop on integrated regional coordination in ICRISAT, India, 25-29th March 2013.

List of Participants

S.No	Name	Address	E-mail
1.	Dr.Apurbo Kumar Chaki	Scientific Officer, On-Farm Research Division, Bangladesh Agricultural Research Institute, Joydebpur, Gazipur-1701, **Bangladesh**	E: apurbochaki@yahoo.com T: +8801722063193
2.	Mr. Md. Raihan Talukder	Scientific Officer, Soil Science Division, Bangladesh Agricultural Research Institute, Joydebpur, Gazipur-1701, **Bangladesh**	E: raihan_soilsci@yahoo.com T: 01714-876966
3.	Ms. Thembeka Mpulsang	Principal Investigator, Botswana College of agriculture, Gaborone, **Botswana**	E: tmpulsan@bca.bw T: 0026773512347
4.	Mr. Tiganadaba Lodoun	Research Assistant, INERA (Institute for Environmental and Agronomic Researches), P.O. Box 8645 Ouagadougou 04, **Burkina Faso**	E: tiganadaba@yahoo.fr T: 226 724166179
5.	Mr. Araya Alemie Berhe	Assistant Professor, Mekelle University, P. O. Box 231, **Ethiopia**	E: arayaalemie@gmail.com T: +251914722576
6.	Mr. Girma Mamo Diga	Agro meteorologist, Ethiopian Institute of Agricultural Research (EIAR), Melkassa Research Center, P.O.Box 436, **Ethiopia**	E: mamogirma@ymail.com T:+258 988809500
7.	Mr. Bright Salah Freduah	Research Assistant, AgMIP-CIWARA, Soil and Irrigation Research Centre, University of Ghana, P. O.Box 9, Kpong, **Ghana**	E: kobebryt@hotmail.com T: +233243028757
8.	Ms. Madina Diancoumba	Research Assistant, University of Ghana, P.O. Box LG 25, Legon, Accra, **Ghana**	E: madina.diancoumba@yahoo.fr T: +233542384546
9.	Dr. Raji Reddy Danda	Director, Agro Climate Research Centre, ARI, ANGR Agricultural University, RajenDr.anagar, Hyderabad, AP, **India**	E: dandareddy009@gmail.com T: 09989625220
10.	Dr. Vellingiri Geethalakshmi	Professor and Head, Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore -641 003, Tamil Nadu, **India**	E: geetha@tnau.ac.in T: 09994433479
11.	Dr. Monalisha Pramanik	Scientist, Project Directorate for Farming System Research, Modipuram, Merrut, 250110, UP, **India**	E: monalishapramanik@gmail.com T: 09045065945

12.	Mr. Burhan Uddin Choudhury	Senior Scientist, Division of Natural Resource Managa, ICAR Research Complex for NEH Region, Umiam Umiam-793 103, Meghalaya, **India**	E: burhan3i@yahoo.com T: 09612252086
13.	Mr. Dileep Kachroo	Professor & Head, Farming System Research Center, Division of Agronomy, Sher-E-Kashmir Univ of Agricultural Sciences & Technology of Jammu (Main Campus), Chatha, Jammu-180 012 (J&K), **India**	E: dileepkachroo@rediffmail.com T: 09419187553
14.	Mr. Sohan Singh Walia	Agronomist, Department of Agronomy, Punjab Agricultural University, Ludhiana, Punjab, **India**	E: sohanwalia72@yahoo.co.in T: 09464760134
15.	Ms. K Bhuvaneswari	Research Scholar, Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore -641 003, Tamil Nadu, **India**	E: bhuvanakutti@gmail.com T: 09976176311
16.	Dr. Sreenivas Gade	Professor (Agro), College of Agriculture, Acharya NG Ranga Agricultural University, RajenDr.anagar- 500030, Hyderabad, AP, **India**	E: gsreenivas2002@gmail.com T: 09000407408
17.	Mr. Vemula Anil Kumar	Senior Scientific Officer, Department of Biometrics, ICRISAT, Patancheru, Hyderabad, AP, **India**	E: Anilkumar@cgiar.org T: 9000488878
18.	Mr. Sridhar Gummadi	Special Project Scientist (climate change & Adaptation), ICRISAT, Post Box 39063, Nairobi, **Kenya**	E: s.gummadi@cgiar.org T: 09492931188
19.	Mr. Benson Mututa Wafula	Principle Research Scientist, Kenya Agricultural Research Institute, P.O. Box 27, Embu- 60100, **Kenya**	E: bensonwafula@gmail.com T: +254-721718582
20.	Dr. Asha S. Karunaratne	CFFRC Associate- Principle Investigator (Crop- Climate Modelling), Crops for the Future Research Centre (CFFRC) Level 2 Block B, The University of Nottingham Malaysia Campus JalanBroga, 43500 Semenyih, Selangor DarulEhsan, **Malaysia**	E: asha.karunaratne@cffresearch.org T: 0094 0718316375
21.	Mr. Folorunso Mathew Akinseye	Research Scholar, ICRISAT, WCA, BP 320, Bamako, **Mali**	E: F.Akinseye@cgiar.org T: +223 78855412
22.	Mr. Sebastiao Inacio Famba	Lecturer, Universidad Eduardo Mondlane, Faculdade de Agronomia e EngenhariaFlorestal, P.O. Box 257, Maputo, **Mozambique**	E: sebastiaofamba@gmail.com sifamba@uem.mz T: +258 823961320

23.	Mr. Alhassane Agali	Scientist - Agronomy, Expert Agronome, en charge de l'adaptation au changementclimatiquedans le domaine de l'agriculture, Centre RégionalAgrhymet, BP: 11011, Niamey, **Niger**	E: alhassaneagali@yahoo.fr T: +227 96593656
24.	Dr. Gideon Olubunmi Agbaje	Associate Professor, Department of Crop Production and Protection, Faculty of Agriculture, ObafemiAwolowo University, Ile-Ife, OsunState, **Nigeria**	E: Dr.bunmiagbaje@yahoo.com T: +234 8056127675
25.	Ms. Sandya Kumari Ariyawansha	Research Officer, Sugarcane Research Institute, UdaWalawe, **Sri Lanka**	E: asandyakumari@yahoo.com T: 071-4444856
26.	Ms. Champa Madhumathi Navaratne	Professor & Head, Dept. of Agricultural Engineering, Faculty of Agriculture, University of Ruhuna, Mapalana, Kamburupitiya, **Sri Lanka**	E: champa_m2004@yahoo.com T: +94 718116982
27.	Ms. Sewwandhi Shashika Kularathne Chan Dr.asekara	MDP Coordinator and Intermediate Research Scientist, Foundation for Environment, Climate and Technology C/o Mahaweli Authority, H.A.O. & M. Division, Digana Village, Rajawella, **Sri Lanka**	E: sewwandhichanDr.asekara@yahoo.com T: +94714529145
28.	Dr. Kanagaratnam Sanmuganathan	Adviser, Sugarcane Research Institute, UdaWalawe, **Sri Lanka**	E: ashanmu@ymail.com 0776951114
29.	Mr. Yasas G. HarischanDr.a	Research Officer, Foundation for Environment, Climate and Technology (FECT), C/o Mahaweli Authority - H.A.O. & M. Division, Digana Village, Rajawella, **Sri Lanka**	E: yasasclmd@gmail.com;yasasgeethall@gmail.com T: +94 717940335
30.	Ms. Punya Samanmali Delpitiya	Research Officer, Department of Agriculture, RARDC, Aralaganwila, **Sri Lanka**	E: punya14@yahoo.com T: +94 771521104
31.	Dr. Sarath Premalal Nissanka	Senior Lecturer, Department of Crop Science, University of Paradeniya, **Sri Lanka**	E: nissankasp@yahoo.com T: 094777801903
32.	Dr. W M W Wijayasiri Weerakoon	Director/ Agronomist, Department of Agriculture, Field Crop Research & Development Institute, Mahailluppallama, **Sri Lanka**	E: weerakoonwmw@gmail.com T: 94715337037
33.	Ms. Wiltrud Durand	Researcher, ARC Grain Crops Institute, Private Bag X125, Potchefstroom, **South Africa**	E: pdurand@mweb.co.za; DurandW@arc.agric.za T: +27 834435583
34.	Mr. Yacob Beletse	Senior Researcher, ARC-Roodeplaat, Private Bag X125, Pretoria, **South Africa**	E: beletsey@arc.agric.za T: 27847451510

35.	Mr. Sixbert Kajumula Mourice	Lecturer – crop physiology, Sokoine University of Agriculture, Dept of Crop Sci. and Production P.O.Box 3005 –Chuo kikuu, Morogoro, **Tanzania**	E: sixbert.mourice@gmail.com T: +255 764979464
36.	Mr. Barnabas Msolini Msongaleli	Ph.D student, Sokoine University of Agriculture, Department of Agril. Engineering and Land Planning, P.O. Box 3000, Morogoro, **Tanzania**	E: barnaba.msongaleli@gmail.com T: +255 754821636
37.	Mr. Patrick Musinguzi	Associate Lecturer, Makerere University, P.O.Box 7062 Kampala, **Uganda**	E: musipato@yahoo.com T: +256 774068824
38.	Mr. Moses Makooma Tenywa	Director, Makerere University Agricultural Research Institute, Kabanyolo, P.O. Box 7062 Kampala, **Uganda**	E: tenywamakooma@yahoo.com T: +256 772827710

List of Trainers

S.No	Name	Address	E-mail
1.	Dr. Dilys Sefakor MacCarthy	Research Fellow, University of Ghana, College of Agriculture and Consumer Science, Agriculture Research Centre, P.O. Box LG 68, Legon, Accra, **Ghana**	E: kpongor@yahoo.com T: 00233244090502
2.	Mr. Nageswara Rao Vajja	Lead Scientific Officer, Resilient Dr.yland Systems, ICRISAT, Patancheru, AP, **India**	E: v.nageswararao@cgiar.org T: 09440482528
3.	Dr. Dakshina Murthy Kadiyala	Scientist – Agronomy, Agro Climate Research Centre, ARI, ANGR Agricultural University RajenDr.anagar, Hyderabad, AP, **India**	E: dakshu2k@gmail.com T: 09618956219
4.	Dr. Dougbedji Fatondji	Scientist Agronomy, Ph.D, Agronomist, ICRISAT Sahelian Center P.O. Box 12404, Niamey, **Niger**	E: d.fatondji@cgiar.org T: +227 94859899
5.	Dr. Balwinder Singh	Post-doctoral Fellow, Crop and Environmental Sciences Division, International Rice Research Institute, Lost Banos, **Philippines**	E: b.singh@irri.org
6.	Dr. Guillermo Antonio Baigorria Paz	University of Nebraska-Lincoln, 823 Hardin Hall, 3310 HolDr.ege St., Lincoln, NE 68583-0968, **USA**	E: gbaigorria@unl.edu T: +1 352 397 6711

7.	Dr. Patricia Masikati	Post-Doctoral Fellow, ICRISAT, Box 776, Matopos, **Zimbabwe**	E: p.masikate@cgiar.org T: +263 712622603

Resource Persons

S.No	Name	Address	E-mail
1.	Dr. John Hargreaves	Crop Modeling, CSIRO, Ecosystem Sciences, 203 Tor Street, Toowoomba, Qld, **Australia** 4350	E: John.Hargreaves@csiro.au T: +61 427881395
2.	Dr. N Subash	Senior Scientist, Project Directorate for Farming Systems Research, Modipuram-250110, Meerut, Uttar Pradesh, **India**	E: n_suby@rediffmail.com T: 09457248070
3.	Dr. Peter Craufurd	Research Program Director, Resilient Dr.yland Systems, ICRISAT, Patancheru- 502324, AP, **India**	E: p.craufurd@cgiar.org
4.	Dr. G Dileepkumar	Global Leader, Knowledge Sharing and Innovation, ICRISAT, Patancheru- 502324, AP, **India**	E: g.dileepkumar@cgiar.org
5.	Mr S V Prasad Rao	Senior Administrative Officer, Knowledge Sharing and Innovation, ICRISAT, Patancheru- 502324, AP, **India**	E: s.prasaDr.ao@cgiar.org
6.	Dr. Ken Boote	AgMIP Crop Modeling PI, 304 Newell Hall, PO Box 110500, Gainesville, FL 32611, **USA**	E: kjboote@ufl.edu
7.	Dr. Gerrit Hoogenboom	Director, AgWeatherNet, and Professor of Agrometeorology, Washington State University 24106 North Bunn Road Prosser, Washington 99350-8694, **USA**	E: gerrit.hoogenboom@wsu.edu
8.	Dr. Cheryl Porter	AgMIP IT PI, Department of Agricultural and Biological Engineering, 243 Rogers, PO Box 110570, Gainesville FL 32611, **USA**	E: CPorter@ufl.edu

This page intentionally left blank

Appendix 2

This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

TOA-MD ECONOMIC MODELING WORKSHOP

APRIL 29-MAY 3, 2013
DUBAI, UAE

ICRISAT UKaid from the British people OSU Oregon State University

CGIAR RESEARCH PROGRAM ON Climate Change, Agriculture and Food Security CCAFS

AgMIP TOA-MD Economic Modeling Workshop Report

Dubai, UAE April 29-May 3, 2013

John M. Antle & Roberto O. Valdivia

Table of Contents

Introduction 2
Summary 2
Summary of Activities and Accomplishments by Day 4
Appendix 1: List of Participants 9
Appendix 2: Fast Track Check List 10
Appendix 3: Flip Chart Summaries 11
Appendix 4: Agenda 12

Acknowledgements

This workshop was possible owing to strategic collaboration between Dr. John Antle, Professor, and AgMIP Regional Economics Team Leader, Oregon State University (OSU) and Dr. P. Craufurd, Program Director for Resilient Dryland Systems at the International Crop Research Institute for the Semi Arid Tropics (ICRISAT). The workshop was planned and executed by Drs. J. Antle and R. Valdivia (OSU). Direct support from ICRISAT was enabled by funding from the research program on Climate Change Agriculture and Food Security. Support of participating Sub-Saharan Africa and South Asia economic modelers was enabled with funding from the UK Department for International Development, in partnership with USDA/ARS. In-kind support was provided by OSU. Thanks to Caleb Dickson for his help during the workshop and for taking notes for this report. This workshop report was prepared by J. Antle and R. Valdivia, with additional inputs from S. Lifson.

1. Introduction

An AgMIP-sponsored workshop on regional economic modeling and impact assessment using the TOA-MD model was held in Dubai the week of April 29 (Monday) – May 3 (Friday), supported by additional funds from ICRISAT and CCAFS, and organized by the AgMIP Regional Economics Team at Oregon State University. The goal of the meeting was to review and build on the fast-track analysis to implement a complete climate impact assessment and technology adaptation analysis for at least one regional case study for each Regional Team (see the agenda attached). The participants at this meeting were the economists who set up and ran the TOA-MD model for their team's Fast Track analysis (see the attached participant list).

2. Summary

This section presents a summary of the key accomplishments, issues and conclusions of the workshop.

Key accomplishments were:

- Fast Track exercises were reviewed and economic components were corrected as needed. A summary of the results to date was produced, however, all of the teams need to finalize crop model simulations before the fast track economic analyses can be finalized – see below.
- RAPS were reviewed and methods for the further development were discussed. A summary of RAPS developed so far was produced.
- Methods for using crop model simulations in economic modeling were discussed and advanced in the course of the workshop. In particular, methods for incorporation of time-variation in yields were developed and tested. Related data and protocol issues that need to be addressed by the AgMIP Leadership were identified.
- Methods for incorporating Livestock components were discussed.
- Fast Track exercises were extended to whole farm systems, and complete climate impact and at least one adaptation scenario were modeled (in some cases, using pseudo-data when crop model simulations were not available). Summaries of these results were prepared.
- The climate change impact exercise was extended to include an adaption analysis (focusing the adaptation strategy on the fast track selected crop).
- Plans for RAPS and modeling methodology publications were discussed.
- In the course of the work, various modeling and methodology questions were discussed.

Key Issues identified:

- Issues related to climate data and crop modeling:
  - In some cases, historical and future weather data did not conform to AgMIP protocols being used by crop modelers.
  - Simulated yield data did not conform to AgMIP protocols for some teams; crop model simulations by some teams were not done with management variation; data were not provided to economists in ACMO format in all but one case; many teams provided data that were bias-adjusted or averaged, rather than native crop model outputs not bias adjusted, by survey farm and by year.
- Issues related to economic modeling were mostly on interpretation of results. However, for some teams it remains to be seen whether the economist(s) are able to conduct analysis independently.
- Issues related to communication and coordination within Regional Teams were identified.

Conclusions and next steps:

The economists agreed to the following approach to advance the Regional Teams' work:

- First, the group agreed that the first RAPS developed should be "business as usual" and then modify those pathways to represent other plausible futures, possibly including "wild card" cases.
- Second, the Fast Track analysis must be completed correctly. The key missing element for most teams is crop model simulations completed according to AgMIP protocols.
- Third, in the opinion of the Regional Economics Team, it is critical to demonstrate the capability of the teams to conduct full assessments as soon as possible. Thus, it is critical for the climate and crops scientists to provide the data needed to complete full impact assessments and adaptation analyses for the Fast Track study areas. To accomplish this, the Fast Track analysis needs to be extended to include the major crops in each of these systems, and simulations need to be completed for multiple climates. With these data the economists can complete a full impact assessment and analysis of adaptations for these study areas. For example, in the Nioro, Senegal Fast Track study done by CIWARA, the Fast Track analysis was based on millet. Two other important crops in this system, maize and peanuts, need to be done for multiple CMIP5 climates, RCPs and future time periods.
- The Regional Economics Team advises that before the July meetings, all major crops in the Fast Track study areas should be completed with at least one CMIP5 climate, for RCP

4.5, for the mid-century period. To accomplish this, the climate and crop modeling scientists will need to complete this work by June 21 for the SSA teams and by June 28 for the SA teams so that the data can be provided to the economists in time for them to complete their analysis and present results at the July meetings. If this is not feasible for all climates and time periods, at least some climates and crop model simulations should be completed according to the AgMIP protocols.

- **To ensure that the work is done correctly, the AgMIP Regional Economics Team recommends that the data should be provided to the Regional Team economists as well as to the resource persons for each team and at least one AgMIP Leader who can verify that the protocols have been followed. A conference call with the lead crop modeler and economist from each team with their resource person and corresponding members of the AgMIP leadership is recommended as soon as possible to ensure intra-team coordination and communication is occurring, and that a plan is in place to meet deadlines for the July meeting.**

In addition, the following actions will be taken by the Regional Economics Team:

- The Regional Team Handbook will be revised to reflect refinements of the procedures for utilizing simulated crop yields in economic analysis.
- The Regional Team Handbook will be revised to update the RAPs development process. The DevRAP matrix tool will also be updated.
- Projected global prices for major commodities will be obtained from the global economic model inter-comparison exercise and included in the Handbook with guidelines for their use.
- The templates for the Fast Track summary reports will be revised.

3. Summary of Activities and Accomplishments by day.

Monday, April 29, 2013

Topics:

- Introductions
- Fast Track Presentations
- Modeling Issues

Summary:
The workshop started with introductions and expectations from each attendee and a statement of objectives from John Antle. Then each team gave a presentation on their Fast Track Reports. These presentations explained the data used and results obtained from TOA-MD simulations. The session concluded with a discussion on data and modeling issues that researchers

encountered. Some examples of these issues included the problems obtaining data from crop modelers, calculating statistics/parameters from the data, dealing with outliers, estimating correlations, setting tradeoff points, and stratifying the data. In addition, John Antle requested all participants to prepare a tentative title for a paper for which they could be lead author.

Regional Teams Presentations:
1. "Climate Change Impacts on West African Agriculture – A Regional Assessment," by West Africa team (I. Hathie)
2. "Modeling the impact of a variable and changing climate on rice agricultural system in Sri Lanka for AgMIP," by Sri Lanka team (Herath)
3. "Modeling the impacts of a variable and changing climate on rice and sugarcane agricultural systems in Sri Lanka," by Sri Lanka team (Dumindu and Erandika)
4. "Impact of Climate Change on Adoption, Income and Poverty," by East Africa team (R. Mulwa)
5. "Integrated Assessment of Climate Change Impacts on Principal Crops and Farm Household Incomes in Southern India (TNAU)," by South India team (Paramasivam)
6. "Integrated Assessment of Climate Change Impacts on Principal Crops and Farm Household Incomes in Southern India (ANGRAU)," by South India team (Sunandini)
7. "Crop Livestock Intensification Project in Southern Africa, Site: Zimbabwe, Nkayi," by Southern Africa-CLIP team (S. Homan-Kee-Tui)
8. "Strengthening simulation approaches for understanding, projecting, and managing climate risks in stress-prone environments across the central and eastern Indo-Gangetic Basin," by North India team (Harbir)
9. "Southern Africa Agricultural Model Inter-comparison and Improvement Project," by South Africa team (Mogos)
10. "Modeling the Impact of Climate Change on Wheat, Rice and Cotton in Pakistan" by Pakistan team (Irfan A.)
11. "The Economic Impact of Climate Change: A Multi-dimensional Impact Assessment for smallholder maize and wheat grown in Ethiopia," by East Africa team (Kebede)
12. Uganda (participant provided an update on progress) (J. Bonabana)

April 30, 2013

Topics:
- Review of Methods for Crop Model Simulations
- Update Fast Tracks

Summary:
The session began with a presentation on relative yield calculations by John Antle. This presentation outlined an approach for calculating future relative and predicted yields that allows for variation across time and space. Next, the regional teams worked on finalizing their fast track reports and performing a simulation with time varying relative yields. This exercise led to the assessment of the type of data economists have received from crop modelers. Some teams did not have the requisite crop modelling data to calculate relative yields for each farm

in each future year (the crop modellers need to provide simulated yields for every site and every year). In order to continue with the exercise these teams generated "pseudo" datasets so they could become familiar with the process they will follow when they have all the data. The teams reviewed their fast track using a checklist to assure consistency and correct model parameterization. Then the teams reconvened and discussed results and issues from the day.

Documents for Appendix:

- Fast Track Review Checklist
- Relative yields AgMIP handbook update

May 1, 2013

Topics:

- Livestock
- RAPs
- Data

Summary:
The session began with a review of the previous day's topics and issues moving forward with economic impact assessment modeling. In particular, John Antle suggested that yield distributions may not be stationary over time and, if this is the case, it may be better to examine shorter time intervals on a year by year basis. Then Sabine Homann-Kee Tui gave a presentation on livestock modeling based on the CLIP's activities. She discussed characteristics of livestock-crop integrated systems, strategies for calculating livestock activities' parameters for TOA-MD, and how future livestock production could be modeled under climate scenarios. This was followed by a demonstration by John Antle on different ways to model and parameterize livestock activities in TOA-MD (e.g. how to input livestock parameters that are in per-animal units). It was noted that the documentation of the TOA-MD model includes technical documents and there is one referred to modeling Livestock. During the second part of the session, the regional teams gave reports on the development of their RAPs. These presentations covered the RAPs meetings, development process, outcomes, issues, and future plans. An update of RAPs methodology was then presented by Roberto Valdivia. Roberto provided an outline for the development of RAPs and proposed that each team develops a Business as Usual RAP as the starting point. The teams agreed to start their RAPs development with a BAU RAP. The day's session ended with team breakouts for finalizing the characterization of each region's system 1 (base climate, base technology) for TOA-MD analysis.

Workshop Presentations:
- "CLIP: Livestock Modeling," by Sabine Homann-Kee Tui.

- *Regional Teams RAPs presentations*
1. South India
2. East Africa (Kenya)
3. Southern Africa (CLIP)

4. Pakistan
5. East Africa (Ethiopia)
6. Sri Lanka
7. North India

- "RAPS, Update on Methodology" by R. Valdivia

Date: May 2, 2013

Topics:

- Translating RAPs into model scenarios
- Team preparation of full systems for Fast Track studies
- Design and implementation of preliminary adaptation Scenarios

Summary:
John Antle started the day with a short lesson on using TOA-MD to assess climate change impacts under different adaptation scenarios. --ADD Figure for CC IA: Base Climate, Base tech -> CC, Base tech, etc..(John's presentation)
Then Lieven Claessens gave a presentation on a study which developed climate change adaptation scenarios for small farmers in Kenya (Claessens et al, 2012, Ag Systems). He described how future scenarios were developed and parameterized for TOA-MD, and how to interpret and explain the results from this type of analysis. Next, the regional teams were given time to develop adaptation scenarios. This exercise allowed teams to practice how TOA-MD is used to analyze scenarios with future climate and technology adaptation. The day concluded with a discussion on publication ideas. John Antle suggested the possibility of a RAPs paper, a yield methodology paper, and a special issue in a journal.

Workshop Presentations:
"A Method for Evaluating Climate Change Adaptation Strategies for Small-Scale Farmers Using Survey, Experimental and Modeled Data," by Lieven Claessens.

Date: May 3, 2013

Topics:

- Adaptation presentations
- RAPs plans
- Publications and Outreach

Summary:
The session began with a short demonstration on examining data by John Antle. Then the regional teams presented reports on their progress from the workshop (the teams followed a template to report the updated fast track and adaptation analyses). These reports included the updated fast track analysis, one adaptation analysis, and publication proposals from each

member of each team. The session concluded with a discussion on how the project will proceed. This covered a to-do list for regional teams and AgMIP economic leadership and ideas for publications and outreach. The tasks for regional teams are to finalize fast tracks, extend fast tracks (multiple crops and climates), complete climate change impact and adaptation analysis for fast track study sites, and complete RAPs; for AgMIP economic leadership the tasks are to revise the AgMIP handbook on yield calculations, plan a strategy to incorporate global prices (e.g. fertilizer and fuel), revise the workshop report templates, and distribute updated DevRAPs. The following publication topics and ideas were proposed: regional RAPs, yield methodology, fast tracks, policy briefs, working paper series, and special issue of a journal. The outreach avenues offered were farmer publications, radio and local press, students (e.g. university seminars), and journalists.

Workshop Presentations:
Workshop reports (includes notes on what needs to be fixed for finalizing)
1. Southern Africa-CLIP (look at future yield calculation, correct labels, interpretation)
2. Pakistan (pseudo data; negative per-capita income, correct labels, interpretation)
3. West Africa (extremely large reduction in yields in future)
4. South India- ANGRAU (expand tradeoff points on climate change assessment)
5. East Africa- Kenya (correctly interpret the fast track results; use the correct system 1 for adoption analysis)
6. Sri Lanka- Rasnaya Herath (interpretation)
7. South Africa- SAMIIP (use correct system 1 for adoption analysis)
8. South India- TNAU (too few observations per stratum)
9. North India (check yield calculations)
10. Sri Lanka- FECTS

4. Planning

- Present at July meeting completed FT case studies with full system, multiple RAPS and multiple climates, mid-century with CC impact assessment w-o adaptation and with adaptation.

- RAPS paper

- yield methods paper

    - matched, time averaged

    - matched, time varying (by year)

    - un-matched (need to work out details)

- reviewing papers? The teams mentioned the need for a systematic way to review papers within AgMIP before being submitted (quality control).

- special issue: (need to finds a journal)

    - Methods

    - RAPs

Appendix 1. List of Participants

AGMIP TOA-MD Workshop

Dubai, April 29 - May 3

Participants List

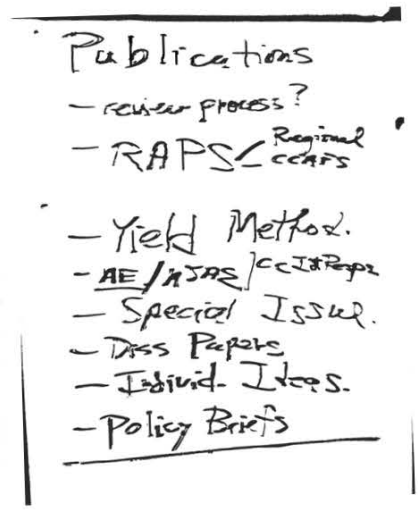
	Name	Project/institution	Country	Email
1	Charles Nhemachena	South Africa	Zimbabwe	cnhemachena@hsrc.ac.za
2	Mogos Teweldemedhin	South Africa	Namibia	mogosteweldemedhin@gmail.com
3	Joseph Amikuzuno	West Africa	Ghana	amikj26@yahoo.com
4	Ibrahima Hathie	West Africa	Senegal	ihathie@yahoo.com
5	Harbir Singh	North India	India	hs.pdfsr@yahoo.com
6	Dinesh Kumar Thapa	North India	Nepal	darlami.dinesh@gmail.com
7	Rasnaya Herath	Sri Lanka	Sri Lanka	herath.rasnayaka1@gmail.com
8	Erandika Wijekoon	Sri Lanka	Sri Lanka	erandikawijekoon@gmail.com
9	Dumindu herath	Sri Lanka	Sri Lanka	duminduherath@gmail.com
10	Sabine Homann-Kee Tui	Southern Africa-CLIP	Zimbabwe	s.homann@cgiar.org
11	Lieven Claessens	Southern Africa-CLIP	Kenya	l.claessens@CGIAR.org
12	Arthur Chibwana	Southern Africa-CLIP	Malawi	arthurchibwana@gmail.com
13	Muhammad Ashfaq	Pakistan	Pakistan	ashfaq9@hotmail.com
14	Syed Asif Ali Naqvi	Pakistan	Pakistan	syedasif_1@yahoo.com
15	Irfan Ahmad Baig	Pakistan	Pakistan	irfybaig@gmail.com
16	Richard Mulwa	East Africa	Kenya	richard.mulwa@yahoo.com
17	Khamaldin Mutabazi	East Africa	Tanzania	khamaldin@yahoo.com
18	Jacqueline Bonabana	East Africa	Uganda	jbexim@gmail.com
19	Kebede Gebru	East Africa	Ethiopia	solomonmanjur@gmail.com
20	P.Paramasivam	South India	India	params@tnau.ac.in
21	R. Balasubramanian	South India	India	rubalu@gmail.com
22	Suresh Kumar	South India	India	rithusuresh@yahoo.com
23	Sunandini Prema	South India	India	sunandinigp@yahoo.in
24	Nedumaran Swamikannu	ICRISAT	India	S.Nedumaran@cgiar.org
25	Caleb Dickson	Oregon State Univ	USA	caleb3105@gmail.com
26	Parakrama Samaratunga	Sri Lanka	Sri Lanka	parakrama@ips.lk
27	Gokul Paudel	CIMMYT	Nepal	g.paudel@cgiar.org
	AgMIp Econ Leadership team:			
28	John M. Antle	Oregon State Univ.	USA	john.antle@oregonstate.edu
29	Roberto O. Valdivia	Oregon State Univ.	USA	roberto.valdivia@oregonstate.edu

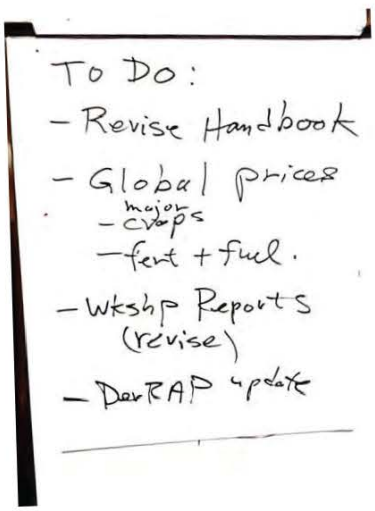
Appendix 2. Fast Track Check List.

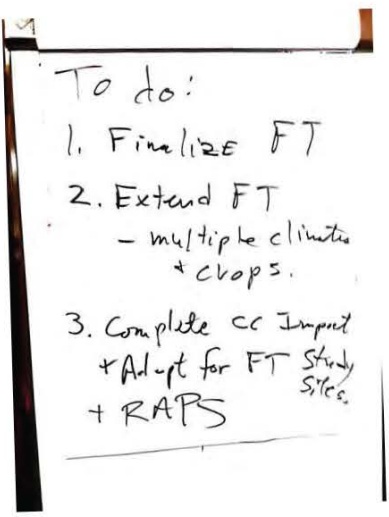
FAST TRACK REVIEW CHECKLIST
TOA-MD AgMIP Workshop, Dubai 2013

1. DATA	CHECK	Comments
- Check actual data for outliers, make histograms	☐	
- Simulated yields distributions	☐	
- Correctly estimate relative yields and predicted future yields	☐	
- Stratification: decide if Stratification is needed/possible	☐	
- Calculate statistics and double check they are correctly estimated (check predicted/modeled standard deviation, CV) - Check againfor outliers, strange values, etc	☐	
- Estimate can make sure RHO12 makes sense	☐	
- Estimate and check values for RHOC1, RHOC2 if needed	☐	
2. MODEL		
Setup:		
- Do_Climate = 1	☐	
- Check units and select appropriate value for C_UNITS, L_UNITS, P_UNITS	☐	
- Check units for CVs	☐	
- Check STD_C, STD_L, STD_P: Standard deviation of NRs	☐	
- Check activity Weights	☐	
- Check fixed costs (are they needed, correct values (check also T1, T2, R))	☐	
- Review all sheets making sure all the values are correct, consistent and in the correct places	☐	
Results:		
- Check Output sheets:	☐	
○ Look for consistency	☐	
○ Check Tradeoff points	☐	
- Interpretation	☐	

Appendix 3. Flip Chart Summaries.







Appendix 4. Workshop Agenda.

AgMIP TOA-MD Workshop Agenda

Dubai, UAE April 29-May 3, 2013

Sunday April 28

Arrivals

Monday April 29 **Review goals, team progress, modeling issues**

8.00	Registration (Meeting Room located in Second floor)
8:30	Welcome and Objectives, Data, Introductions
9:00	Team presentations
10:00	Break
10:20	Team presentations
12:00	Lunch
1:00	Team presentations
3:30	Break
3:50	Discussion of modeling issues
4:30	Review agenda and plan workshop products
5:00	Wrap up: plan for Tuesday

Tuesday April 30 **Finalizing Fast Track**

8:30	Review methods for using crop model simulations (JA)
10:00	Break
10:20	Team breakouts – update fast track
12:00	Lunch
1:00	Continue breakouts/discussion of results
3:00	Break
3:20	Present new results & discuss
5:00	Wrap up – dinner logistics
7.00	Group dinner – depart hotel by bus

Wednesday May 1 **Livestock, RAPS & Data**

8:30	Methods for Livestock (Sabine & TOA team)
10:00	Break
10:20	Livestock plans - discussion
11:00	Reports on RAPS
12:00	Lunch
1:00	RAPS methodology discussion, update
2:00	Whole farm data cleaning, setup (assignments of variables)
3:00	Break
4:00	Data examples & discussion
5:00	Adjourn

Thursday May 2 **Teams design and implement adaptation scenarios**

8:30	Adaptation example: Kenya example
9:30	Prepare adaptation exercise
10:00	Break

10:20	Teams breakout for adaptation exercise
12:00	Lunch
1:00	Teams continue
3:00	Break
3:20	Teams continue
5:00	Wrap up

Friday May 3 **Teams present adaptation scenarios and results, discuss plans for RAPS, publications and outreach**

8:00	Team presentations and discussion
10:00	Break
10:20	Review the Economic Protocol
12:00	Lunch
1:00	Meeting report completion, and planning for July meetings
2:00	Planning: Publications (methods paper, RAPS paper, special issue)
3:00	Adjourn

This page intentionally left blank

Appendix 3

This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

SUB-SAHARAN AFRICA MID-TERM WORKSHOP REPORT

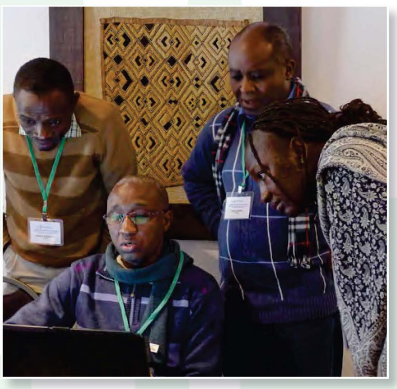
REGIONAL INTEGRATED ASSESSMENTS

JULY 15-19, 2013
PRETORIA, SOUTH AFRICA

UKaid from the British people

CIAT 45 Centro Internacional de Agricultura Tropical International Center for Tropical Agriculture

USDA



Report of the AgMIP SSA Mid-term workshop on integrated regional assessments,

Held on 15-19th July 2013,

Pretoria, South Africa

Prepared by the SSA AgMIP coordination team led by Job Kihara, International Center for Tropical Agriculture (CIAT)

25/August/2013

Acknowledgements

This workshop was made possible by support from UKAID and institutional support from CIAT. Organizational support was provided by Yacob Beleste, Agricultural Research Council in South Africa and Julie Ogola, CIAT. Workshop report was prepared by J. Kihara and Yacob Beletse with additional inputs from S. Lifson and C. Mutter. Thank you to AgMIP PIs and Leadership for their contributions to the program and planning and execution of the Workshop. Thank you also to the regional stakeholders for their generous time and participation.

Table of Contents

Introduction 3
Opening ceremony 3
Opening speech by Agriculture Research Council -CEO Dr. Shardrack 3
Progress reports of Regional Research Teams and Coordinating Research Team 4
Afternoon breakout 6
Stakeholders' deliberations with SSA AgMIP coordination and leadership 6
Stakeholder perspectives from Zimbabwe 7
Stakeholder perspectives from Kenya 7
Stakeholder perspectives from Botswana 8
Stakeholder perspectives from Mozambique 9
Stakeholder perspectives from Malawi 9
Stakeholder perspectives from South Africa 9
General discussion on AGMIP stakeholder engagement (Plenary) 10
Climate breakout 11
Crop modeling breakout 11
DAY TWO 12
CLIP meeting with stakeholders 12
SAAMIIP meeting with stakeholders 12
EA meeting with stakeholders 13
Crop modeling session 14
Climate team breakout 14
DAY THREE 14
Field Trip to Brit area and Hartbeeespoort dam 15
DAY FOUR 16
DAY FIVE 17
East Africa presentation at plenary 17
SAAMIIP presentation at plenary 18
CLIP presentation at plenary 19
CIWARA presentation at plenary 19
KEMIC presentation at plenary 19
Final highlights and feedback from leadership 19
Appendix 1. Workshop program 21
Appendix 2. Participant list for the SSA Midterm workshop in Pretoria 25
Appendix 3. Stakeholder biographies 28
Appendix 4. FAQs 29
Appendix 5. Mid-Term Workshop Checklist 31
Appendix 6. FTP site naming conventions 34

Day One

Introduction

Climate change continues to be a key challenge to food production and possess serious threats to food security. AgMIP has continued with integrated regional assessments in sub-Saharan Africa through its four regional research teams and a coordination team. As part of the series of AgMIP's planned three workshops, this report provides highlights and key discussions of the 2nd workshop for SSA-wide AgMIP teams. It was attended by 70 participants including 10 members of the AgMIP leadership team, 4 resource persons representing the Regional Research Teams (RRTs), 6 members from SSA coordination team (CRT), 6 members from CLIP and 14 from SAAMIIP (both from southern Africa), 13 from East Africa AgMIP RRT and 12 from CIWARA (West Africa). In addition, there were 6 stakeholders. The first workshop (Kick-off) had been held in Accra, Ghana in September 2012.

Opening ceremony

Dr. Yacob Beleste, the Host Regional Research Team PI started off the meeting and Jim Jones, who welcomed everybody to the mid-term SSA workshop, led participants in short individual introductions and then introduced agenda for the workshop and for the day. Workshop goals were to:

1. Demonstrate the accurate completion of the mid-term workshop checklist
2. Work together on multidisciplinary analysis of simulation results
3. Ensure that each team has clear work plan to achieve full project goals
4. Work on post-fast-track integrated assessments, analyses, and discuss targeted publications
5. Develop plan for dissemination of AgMIP results to inform stakeholder actions

Detailed workshop program is in appendix 1.

Opening speech by Agriculture Research Council -CEO Dr. Shardrack

Dr. Shadrack welcomed participants to the Republic of South Africa and challenged the participants on the need to ensure sustainable food security for the growing current and future populations. He emphasized that the right data and tools are needed to come up with solutions required to meet the production needs and that AgMIP is well suited to help with this. He mentioned that as a research council (i.e., ARC), they want to be part of this process towards understanding implications of climate change. He wished the team productive discussions and success to generate the kind of information required in order to have productive ecosystems. He finished by asking AgMIP to take advantage of ARC's collaborations in forging ahead and for success of this project, and that they are grateful for AgMIPs choice of South Africa as venue for the meeting and looking forward to participating in this project through future collaborations.

Cynthia Rosenzweig presenting "the state of AgMIP".

Cynthia Rosenzweig then talked about "the state of AgMIP". The Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications was introduced and plans for a second book were given. Regional PIs were invited to present their draft chapters in Tampa Florida, early November 2013. Cynthia Rosenzweig 's presentation focused on the global modeling work. AgMIP has wonderful links with other initiatives such as CCAFS. AgMIP has already developed methods for integrated regional assessments (IRA). Key results with RCP 8.5 and 20 GCMs for temperature and precipitation were shown. There is quite some uncertainty with regard to precipitation. Lessons learned in AgMIP were shown.

Current results from AgMIPs' global modeling work indicates that median of crop ensembles reproduces observed yields well. It was noted that to have rigorous results, best practices in model calibrations are essential. Key sources of uncertainty were presented and AgMIP is working hard towards this. Another important although preliminary result shown was that 9 models show that agricultural prices are projected to go up. Participants were invited to join any of the groups involved with crop model improvements.

Discussions following the highlights of global modeling raised a question of data quality. Farm survey data is not part of what is considered platinum, gold or silver, but is nevertheless important for AgMIP's integrated regional assessment (IRA) work. Another aspects was that AgMIP global modelling is currently leaving out farming systems level component by looking at individual crops, and noting that we should be concerned about other components of food security including nutritional food security i.e., rather than the traditional crop by crop/ component modeling.

Progress reports of Regional Research Teams and Coordinating Research Team

Each of the RRTs and CRT made presentations of their progress with the fast track. AgMIP eastern Africa had observed that wetter areas show yield increase while projections for dry areas show decrease in

most cases, as expected. The need to get crop, climate and economic modelers to understand results of each other was noted, i.e., intra-discipline understanding since crop modelers showed difficulty understanding results from economists. Other observations include:

- Climate scenarios are the key drivers of the modeling so this needs to be presented in more details (i.e., include also summary statistics), to help in interpreting the results. Further reasons, say for example, why the results from RCP 4.5 and RCP 8 are different should be provided. Is this the strong effect of CO_2 in one case as opposed to the other?
- Clearly differentiating stakeholders for communication/dissemination and for RAP development (these are 2 parts of the stakeholder process) is important.
- In AgMIP, large groups framed the RAPS while small groups targeted/nailed them. It is cutting edge scenario development.
- In bringing stakeholders, we are asking them to help us, not the other way. This is an effective way to draw stakeholders early on in the project. They can then take ownership of the results and help to disseminate.
- How do we document and archive our RAPs?
- For ECOWAS region, need to include Nigeria, as the bread-basket, in future work to ensure wide dissemination in the region.
- How do we groom young scientists? We need to see what to do to have a critical mass of scientist doing modeling. There is interest to see new blood in the system for sustainability of modeling work. The BMGF are interested to see more young professionals as more people get engaged in the assessments. A photo of young scientists (40 years and under) is below.
- Good agronomic management could be better than fertilizers. We need to see how the model can focus on agronomic management within current climate (planting density, manure together with fertilizers). Climate change is not in some cases the most important driver so would be interesting to see presentation of climate scenarios. This is mainly a matter of presentation of results since some of these are already being modeled.
- Economic results should be easy to understand for everybody so need to condense and aggregate that data into ways that are understandable. More creativity is needed here. It was however clarified that some of those economic graphs as presented are diagnostic tools for researchers and are not meant for stakeholders.
- There is need to include who the winners are when we show cases of winners and losers.
- Data are showing that sensitivity to CO_2 and temperature is the same whether yields are high or low. But also, High CO_2 has a direct impact on transpiration and in DSSAT, there is a significant effect on yield. High CO_2 shows a much higher effect in DSSAT than in ApSIM.
- AgMIP is building capacity for assessments of all kinds including agronomic management. This week, we look at what set of experiments we are going to focus on, going beyond the fast track.

A stakeholder raised the following concern "at different crop stages, we get dry spells. How do we build these into the crop models?"

Ken Boote: crop models are already taking care of this since they are dynamic. The challenge is how well the models are doing this. John Antle: interesting question would be "How are the in-season variations being reflected in the modeling?"

Young Scientists (under 40) at the SSA Mid-Term Workshop.

Afternoon breakout

Interdisciplinary team breakouts for Monday afternoon were organized to:

1. Present the mid-term checklist in details.
2. Determine methodological challenges about data and modeling.
3. Share experiences and lessons.
4. Prioritize work while being realistic and to support each other to become collectively stronger.

Stakeholders' deliberations with SSA AgMIP coordination and leadership

The coordination team together with some of the AgMIP leadership held discussions with 6 stakeholders derived from Malawi, Mozambique, South Africa, Kenya, Zimbabwe and Botswana. Brief biographies of these stakeholders are in Appendix 3. The purpose of this session was to give an opportunity to stakeholders to give AgMIP some feedback on the work of the RRT as presented in morning session, and to find out what are the concerns/expectations of the different stakeholders. Although stakeholder linkage had not received much attention earlier on, teams need to link with stakeholders much more and as part of future project proposal. The objectives or key questions of the session were:

1. What you are thinking on what AgMIP is doing and how would AgMIP help in your country?
2. Provide an inventory of key projects in your country on climate change that you think AgMIP should link/collaborate with.
3. What are your concerns for AgMIP to solve with regard to food security issue in your country and the needs of policy makers?

4. What are your suggestions of best ways for AgMIP to disseminate research outputs in your country?
5. What questions do you have for AgMIP?

Stakeholder perspectives from Zimbabwe

The stakeholder is involved in monitoring of agricultural production and mobilization of farmers towards yield goals and food security, in promoting climate-smart agriculture and at the national level, one of 8 persons responsible for climate aspects, disseminating agricultural-extension messages, informing about year by year production, working on dissemination strategies for technological interventions (including mass media and other ICT methods). Initial involvement in AgMIP in Zimbabwe was in developing scenarios but need more involvements in terms of national climate action plans (interface between government and AgMIP).

AgMIP will help answer a lot of questions. What do we do to address climate change issues and meet food security for the many households who depend on agriculture for livelihood? AgMIP modeling will come up with solutions for food security and adaptation by offering best managements. For example, farmers need to make choice of how to target fertilizers, at planting or at top dressing given the little resources available. In packaging technologies, it is needed to know who the players are, what infrastructure are available, accessibility of radio, extent of network coverage among others. Packages can be written for farmer groups that are literate but those not so literate ones may need on-farm demonstrations. Thus, (1) farmers will learn, (2) AgMIP will provided needed guidance on how to do better farming, and (3) AgMIP will advice on most profitable solutions including combinations of management for climate versatility.

Agro-ecological zonations in Zimbabwe were prepared in 1960 and are now being revised involving work between climatologists and agro-meteorologists and looking at scenarios for different regions. National climate change action plan is in the making. AgMIP can assist with information to come up with concrete plans. Also, drought-monitoring center (regional center based in Harare for SADEC zone) is modeling seasonal predictions and providing advice for farmers. Here, synergy with AgMIPs research is needed.

Other areas of concern and where stakeholders and AgMIP scientists can work together include supporting the inadequate socio-economic data, building local capacity to do AgMIP-type of modeling at the national level, engaging many stakeholders so we improve quality of our economic models, exploit the fact that, due to high incidences of crop failure, farmers are keen to listen to and try out tangible solutions and AgMIP can to fill in this information requirements. Final question is 'How do we build in the local knowledge systems? '

Stakeholder perspectives from Kenya

The stakeholder is responsible for climate change and adaptation and participated in preparation of National Climate Change Action Plan, which was launched this year. A national adaptation plan is in the making. Ideas have been endorsed by Cabinet and are captured in Vision 2030. Clean and healthy environment is a key goal in Kenya. For the first time, Kenya's' 5-year action plan is having climate

change adaptation and mitigation issues integrated. Once mainstreamed in national planning, it will influence budgeting.

Stakeholder's work also includes knowledge management and capacity building. Although doing well, the country is not there yet. Stakeholder participated in AgMIP eastern Africa teams scenario setting in Kenya (the RAP process) where the team was asked to go beyond maize and include beans, commonly used and also since farmers are concerned about nutrition and food security in event of drought affecting maize. Thus, now Eastern Africa AgMIP team is now taking up beans in the modeling. There is need to consider policy instruments and interventions that are in place currently when moving on with AgMIP project. A key concern is the need to see movement from piloting to implementation to ensure that what we are doing is touching the ground somewhere and have a feel of what is happening in a feedback mechanism. Stakeholder does not want AgMIP to become an academic exercise as many other projects are.

Stakeholder was a member of MET's "Communication, outreach and public information". Media is a big opportunity for public awareness and sensitization.

It was noted that socio-economic outputs can help in specific policies and stakeholders were asked to be very specific so that their need can be included in the TOA models. Since some country teams are behind in the IRA, the need to learn from successes of other teams was noted.

All stakeholders were requested to provide the RCT with information at the national level including copies of the climate change action and adaptation plans, regional level projects and initiatives etc.

Stakeholder perspectives from Botswana

Botswana stakeholder is part of national climate change committee that is guiding government on climate change issues and advising ministry of agriculture on adaptation to climate change. He had not been involved in AgMIP previously. Challenges for AgMIP in Botswana: how will production systems respond to climate change? This information is not readily available. AgMIP is not strong in Botswana with only one person participating (need to involve more persons) and not addressing livestock sector which is very important. There is need and opportunity for capacity building in AgMIP type of integrated regional assessments (i.e., plan to train modelers). Also, lessons from Zimbabwe on aspects such as livestock can be transferred to Botswana. Moving forward, there is need to create more awareness of the AgMIP project to increase its visibility. Botswana is promoting specialized farming (i.e., zoning regions for specific commodities), and AgMIP can help us on suitability of areas for specific crops. Policy makers in Botswana would want to know, for the different productions systems (communal, rangelands), who will be winners or losers in order to target adaptation interventions. In terms of outreach, the stakeholder could facilitate a meeting for presentation of AgMIP project approach and results to the research team in Botswana. Botswana is also ready to collect data needed for AgMIP type of modeling in Botswana (so they need to know what is needed) and these data can be used to build capacity in future. Botswana will follow AgMIP scientists to help with crop-livestock interactions. AgMIP was invited to use Botswana to test the models.

Stakeholder perspectives from Mozambique

Drought and limited investment in dry land agricultural research are key challenges facing Mozambican policy makers while planning interventions to support farmers, mainly small-scale farmers. They need advice and information on simple/cheap technologies that can be accepted, are profitable and adoptable (farmers are resource constrained). Advice on varieties is also sought. The stakeholder has had previous interactions with AgMIP through a project on innovation platforms together with ICRISAT. AgMIP type of research is not as such in progress and also Mozambique has a weak research group. There is no crop insurance system in place.

Stakeholder perspectives from Malawi

The Malawi stakeholder first got information about AgMIP through a crop residue use project he coordinated that included some AgMIP scientists. Malawi has a National Adaptation Program of Action (NAPA) developed in 2006 in response to global concerns (in Ministry of energy and mining) and addresses issues of climate change and adaptation measures in 8 sectors. There are also several projects by NGOs and government ministries on climate change aspects. These include a recently initiated NORAD project to build capacity for managing climate change in Malawi, a DFID project of NAMA dealing with land-use and modeling, a World Bank's big initiative on land use assessment and options targeting vulnerable areas among others. Several other NGOs have projects on climate resilient activities, e.g. conservation agriculture but these are often one-sided (not integrative). These NGOs talk integration but implementation is disintegrated due to their competition. But AgMIP has good integration between the different disciplines and sectors.

Integration of science with development: AgMIP and the other projects dealing with climate change are not seen as talking to each other and this is needed. AgMIP has the advantage that it is research-oriented and the other projects are development-oriented, so AgMIP should inform the development projects of the NGOs in terms of the best technologies for promotion, and to ensure AgMIP is not an academic exercise. There are ongoing thought to establish a committee on technology generation and dissemination. There are many scattered projects yet dissemination is not much in Malawi as in many countries in the region.

AGMIP publicity is low in many countries, i.e., AgMIP is little known. The website is one channel but only technocrats can make use of this. There is need for development of simple briefs that translate the research outputs and that can be handed out. There are opportunities for communication/ dissemination of results using local fora and also "farmer voice radio" (in Malawi) that promotes technologies and, in Malawi, farmers like it.

Stakeholder perspectives from South Africa

The stakeholder is new to AgMIP and joined department of climate change recently. South Africa has gazetted Climate Change Sector Plan for public comments and inputs. The key challenges as presented in this plan include creating awareness on climate change, improving knowledge on climate change, increasing capacity to respond to climate change impact, research and funding of research projects. A "Climate Change Adaptation and Mitigation Plan" has been developed and now distributed to the public for comments, and before moving for approval by the minister. Also, REDD+ preliminary plan has been

developed and is being continuously updated and aligned to reflect the UNFCC REDD+ negotiations. Several projects on climate change issues have been commissioned e.g., crop suitability over SA for future climates with ARC. Key concerns are that Northwest province of South Africa was declared disaster prone and AgMIP can advise on appropriate management; need to ensure food security for the increasing population and, need for solutions for adaptation strategies for climate change. Suggested communication of AgMIP research results is through awareness workshops that include extensions and farmers.

Stakeholders answering questions in plenary.

General discussion on AGMIP stakeholder engagement (Plenary)

AgMIP should do research for impact working closely with stakeholders. Translation of information that is scientific to policy format is challenging and AgMIP would like to work with the stakeholders on this. It was unanimous that we need to communicate in a way that is attractive to the audience, not to justify our approach and model fitness, but simple understandable way. All research should have outreach component and, "farmers learn better from their fellow farmers". Channels for dissemination of results are there and AgMIP just needs to explore them and learn how to talk to the community. Stakeholders will provide documents from their countries that are related to climate change action and adaptation plans and food security so that AgMIP scientist can understand what is in the national action plans. This way AgMIP can contribute to the country issues of food security.

Stakeholders should be treated as important persons, who know their country policy situations well, so that they give the information sought. AgMIP should let stakeholders know that without them, there is a missing link and there is no other way to get the information. AgMIP products must be tailored to fit the different categories.

Stakeholders without much previous contact with AgMIP learned of the great potential in AgMIP. AgMIP technologies need to be categorized to implementation capacity since different countries are at different capacity levels.

AgMIP scientists enquired on the type of stakeholders consulted when coming up with the nation climate change action plan as already done for Kenya. This was explained to include stakeholders at all levels; representatives of ministries, other government institutions, NGOs +CSOs (WWF, Kenya climate change working group which is over 300 NGOs), academia, common men and women through country stakeholder forums. We have ownership at all levels. On timing for policy reviews for adaptation, it was noted that this depends on the product in question. Some products will find ready application but others may require policy intervention. In Mozambique, as in many countries also, management recommendations are designed based on the seasonal forecasts.

Another concern was about the scope of our stakeholders and when farmers should be integrated. Farmers are our stakeholders and we have to be concerned about them. But AgMIP as a research project cannot reach so many farmers so we reach the organized stakeholders and groups that can reach out more farmers. But farmers are needed to inform on what AgMIP is doing and incorporate the farmer's perspectives (i.e., take into account farm community concerns to feed into the models).

Climate breakout

This was chaired by Alex Ruane and discussed problems with climate data analysis. The discussion was basically on the problems climate group is encountering when dealing with their data as well as highlights of new scripts that runs with R, yet to be provided.

The following were discussed:

- Best way of displaying/presenting climate data as may be required by stakeholders
- Climate modeler's use of climate scenarios: One model cannot present well the future scenarios. At least five cases need to be considered for a better decision. In addition to the mean/average from scenarios, new scripts will include standard deviations and number of rainy days and will be released soon
- Improvement of the script that runs the climate scenario analysis
- Dealing with data quality control and missing data, where at least 20 years of data is considered reasonable for use other than <15yrs.

Crop modeling breakout

- For which production systems can a full economic analysis be done? (System includes full complement of crops for a location). Economists want major crops that would represent a household's income.
- If not doing livestock modeling, still need to represent livestock in the economic income. Used literature approach in recent paper (used those estimates for the livestock component).

- During group workshops (boot-camps) could have virtual workshop with leadership components on call.

These breakouts continued also during day two so additional highlights are presented under day 2 and subsequent ones.

DAY TWO

Jim Jones introduced the agenda for Day 2 that was:

- RRT interactions with stakeholders
- CRT facilitates stakeholder interactions and learning among groups
- Leaders review and evaluate progress of each team

The need for team integration was emphasized to ensure that crop modelers and climate persons understand interpretations and understanding of the economic results. Interpretation of results will be key across all teams. Each RRT had their breakout meeting with stakeholders from their regions and discussed further work and existing opportunities.

CLIP meeting with stakeholders

The team went in-depth on the issues discussed the previous day at the stakeholder engagement with CRT, including specifics of NGOs', existing projects etc. In Malawi, areas for dry land grazing are being converted into cropland and there is need for models on crop-livestock integration with the aim for intensification. This is a way to avoid conflicts between livestock and crops. I.e., need intensified systems. Civil society Agricultural network (CISANET), NASFAM, FUM, etc. are working in Malawi and need to be analyzed to understand their bias areas. CISANET is the key forum that AgMIP can use to disseminate the research results in Malawi. Key technologies being advocated do not include livestock, yet these should be integrated, thus CLIP project can help with advice on how to do this. Revision of National environment action plan was done. Existing collaboration framework between IFRI and ministry of Agriculture can be used by AgMIP to disseminate research results, taking advantage of forums organized periodically. National meetings held annually in Zimbabwe are also forums for dissemination AgMIP results.

Names of organizations and platforms where climate change and adaptation can be discussed were prepared for each country. The team also evaluated, for each target country, who will do what.

SAAMIIP meeting with stakeholders

SAAMIIP circulated a document to know what each person can achieve in the remaining project period. Looking where the team is and what it can do, looking at each country's regions and sites and listing their data availability. They also discussed with stakeholders how it can influence policy through this project.

SAAMIIP team and stakeholder (far left).

EA meeting with stakeholders

The chair gave an overview of the previous day and goal of the breakout as (1) looking at the interest of and views from the stakeholders present (2) going through results already obtained and relate them to local community and policy maker's needs throughout AgMIP's period and beyond, (3) review of RAPs and (4) recap of yesterday's disciplinary group discussions (Economics, Climate and Crop Modellers).

This team mentioned the need to look at in-season variability.

If farmers maintain the same technology, there are only marginal changes. Let's see the RAPs, how you developed them and how they could be developed in other countries. We need to know what are the alternative agricultural pathways and what adaptation strategy and how do we translate this into our models. How many RAPs in Kenya, and what assumptions, planting windows, fertilizers and amounts being used? How much are these influenced by the RAPS? Team members in different countries are not at the same level and need to learn from Kenyan group that already went through the RAP development process.

Uganda identified key stakeholders to invite for the RAPS but is waiting for facilitation from PI in order to do that. RAPS in Tanzania will be in August and a follow-up dissemination meeting (netting wider to stakeholders) could be in September. Ethiopia prepared preliminary RAPs and now preparing to hold a stakeholder session for RAPs in August. In Kenya, team will convene national stakeholder session (policy makers) before even sharing results widely with other people. Participants will include those from the regions in the country, targeting agriculture.

CIWARA was not represented (i.e., no stakeholder from West Africa).

Crop modeling session
(Tuesday afternoon, i.e, program changed to thematic breakouts)

Data presentation and interpretation was discussed, stepping through the slides of each individual RRT. The need for a standardized template or example of each of the figures needed by the teams was raised and the RCT could coordinate this. Ken Boote and Alex Ruane would be preparing example slides based on the best graphs from the team presentations of day 1. One key challenge is how to take care of inter-annual variability and farmer to farmer yield variability in reporting. Three key presentation ideas include:

1. Standardized reporting: model calibrations to be reported with observed (the independent) on x-axis while simulated (dependent) are on y-axis. Both axes should have same extent for comparisons. Show always RMSE. Include a 1:1 line in the plots.
2. Survey data: Show probability of exceedence graphs for survey data as these are good. Need consistency in colors for a given model throughout. Include some documentation of the survey for example and be openly transparent on the causes of the deviations in yields for survey data.
3. Baseline and scenario simulations: Use boxplots and whiskers for simulated scenarios (see last slide of CIWARA day 1 presentation) including baseline and future climate for each model. Also, for several different scenarios, yield gains/losses can be shown as a ratio using % increase or decrease in yields. See example from AgMIP-EA.

Besides, rainfall from EA group was presented as boxplots and was applauded as example for all teams. On some aspects, such as livestock results of CLIP, specific teams will decide on presentation of the results. Other general issues include the need to show standard errors when reporting averaged yields. For observed vs. predicted plots, show many points, not just 2 or 3 points on a graph.

Climate team breakout
Alex Ruane discussed with the group on best way of providing guidance to modelers on scenarios selections and best way of presenting climate results to stakeholders. He introduced and shared with the group, scripts and papers that can help the group in presenting and interpreting results. The scripts were made in the way that users can modify them simply.

DAY THREE
Day 3 started by a presentation by Jon Antle on economics focusing on impact and adaptation analysis. This demonstrated theory behind analysis of impact without adaptation as well as adoption of an adapted technology, and asking how this new technology will work in the future climate. TOA-MD is designed to do this type of experiments, looking at technology adoption/adaptation and the resulting impacts. Of the two types of variability, (i.e., temporal and spatial), spatial variability was described. As expected, there are heterogeneous populations in a landscape and we need to stratify these populations by looking at their distributions. Climate change assessment without adaptation is assessed as value of current climate and technology minus value of future climate and same technology. From the distribution of the resulting ω, one gets the losers and gainers for this technology under the future

climate by analyzing the area under the curve. For recap on these and testing technology adaptation (future technology), estimation of ω and the variance of the distributions.

Economists don't want bias-adjusted yields; rather they want to see raw data. For example, if crop modelers bias adjust s1 differently from s2, this violates assumption of the economic model.

Breakouts: RRTs continue with meeting as yesterday afternoon.

Field Trip to Brit area and Hartbeeespoort dam

Afternoon field trip was fantastic. Thirty-five participants joined in this trip that included a visit to one large-scale farmer where farming is highly optimized in terms of irrigation and nutrient applications. Irrigation is done when the automatic moisture meters indicate the need for this. The farm has up to 40 moisture meters installed. Maize yield is 15 t/ha in this semi-arid environment compared to ~1.7 t/ha average for sub-Sahara Africa. The visitors had an experience seeing the packaging and branding of sweet potatoes direct for supermarkets. A second farmer, 20 km further, is growing beetroots and cabbages using both flood and drip irrigation systems. This is at relatively smaller scale than the first farmer and the produce is usually bought by large-scale farmers who have better market access. Nutrient deficiency was visible including very non-uniform crop stands. The trip ended with a visit to the Hartbeeespoort dam supplying water to the irrigation farms.

Workshop participants at small scale Brit area farm.

DAY FOUR

Jim Jones and Cynthia Rosenzweig introduced goals for the day jointly. The teams spent the morning sessions discussing project issues, reviewing progress, prioritizing activities and developing their work-plans for the remaining project period. Part of the prioritization includes selection of key sites that will be taken through the full set of the simulation exercise. To build on what individual teams are planning, and to provide guidance on an appropriate approach, a separate meeting of the AgMIP leadership, RRT PIs and ARPs was convened at noon to discuss the final "home stretch" in the current phase of the AgMIP project and presented to all participants in the afternoon plenary. Here, the key and Core Questions for Integrated Regional Assessment that RRTs need to address in the simulations were introduced as follows:

1) What is the sensitivity of current agricultural production systems to climate change? For these, current production system is simulated under current climate (1980-2009, simulation 1) and under future (mid-century) climate (2040-2069, simulation 2). Here, adaptation is not considered. The two simulations will be compared through a TOA economic simulation without RAPS.

2) What is the impact of climate change on future agricultural production systems? This is looking into the future. The key issues that we want to address are closely related to Global RAPs and SSPs, and regional RAPS need to incorporate these global productivity trends. The regional analyses should be consistent with the global pathways. The two simulation sets here are "future without climate change" and "future with climate change". Here, the economic analysis requires the crop/ livestock simulations 1 and 2 as in question 1 but in this case with RAPs.

3) What are the benefits of climate change adaptations? This is a key question that stakeholders are asking. They want to know the adaptation options and measures and their economic benefits or value. Here, we look at future climate without adaptation (current production system with trend) and with adaptation (climate-adapted production system with trend). The economic analysis here is TOA with RAP for the no adaptation case and TOA with RAP+adaptation for the second case.

These questions basically help RRTs to move from the fast track to the 'home stretch'. Previously and as part of the fast track, teams had been collecting data, cleaning those, developing tool for IT and climate and fata conversion aids. Teams are then ready to deploy these tools to answering the core questions. The specific climate scenarios required for the core question simulations were explained (RCP 8.5, mid-century, 5 GCMs, Delta scenario, and all farms) but noting also that to assess the broader uncertainty of climate change projections, the 20 GCMs will then be used. It was appreciated that the selected 5 GCMs may not represent the most extreme GCMs for all regions to capture the variability in these but are nevertheless good to allow cross-region comparisons of GCM behaviors. Also, components of the adaptation package in the crop/livestock model were discussed as well as how many of these models are required. From the economics side, a key methodological question is how RAPS will incorporate global and regional drivers, and teams will figure out themselves how to capture this. An IT issues is about organization and execution of large number of simulations. The core questions and frequently

asked questions discussed are available here (see Appendix 4 for FAQs). The scenarios described here and the GCMs are only the core and therefore not restrictive thus RRTs are free to do more than this minimum.

John Antle and Alex Ruane will provide details and algorithms for generating the future projections for the economics part.

See appendix 5 for protocols for naming conventions for data posted to the ftp site.

KEMIC plan is to finalize calibration of SC 627 using data for Nkhata Bay, and use sentinel approach to model climate and soil combinations of Malawi that will be compared with the gridded approach that the team already planned to conduct. In the sentinel site approach, each zone will have a representative climate station and representative soil types (soil being from different sources such as ISRIC-WISE, AfSIS e.t.c), representative management (but could also run different sets of management based observed distributions e.g. on planting dates and fertilization). The two approaches needs to go in tandem otherwise just following on the sentinel site if the gridded approach will not suffice is no good. Following KEMIC's experience, the team recommends that AgMIP explore the need for capacity development for SSA in gridded approaches to scaling up of modeling results. This is best as long-term program where capacity is developed based on university training for PhD.

SAAMIIP breakout
Team discussed using district-level yields as matched case (or quasi-matched case). It also discussed RAPs, noting the need to "be creative." Crop modeling team and economic team need to agree on RAPs and explicit implications for crop modeling for adaptation/future technology.

DAY FIVE

Teams were dismissed to the regional team breakout sessions. IT also had a session.

East Africa presentation at plenary

Team showed disagreement in DSSAT and APSIM models and then presented what they can achieve by February 2014. Each country came up with targets. Achievement will include completion of quality control checks, preparation of a comprehensive report with visualizations, selection of GCMs that represent the range of conditions. A set of 6 simulations that will be conducted were provided.

IT team within this RRT will finalize scripts and programs to set up runs, analyze data and develop visualizations, finalize database and continue populating RRT website and blogs although team is poor on this. Home stretch will include all countries. With an extension, analysis will be extended to include all 20 GCMs, extend to other regions, include more raps, more crops, cover more downscaling techniques, and include more crop models.

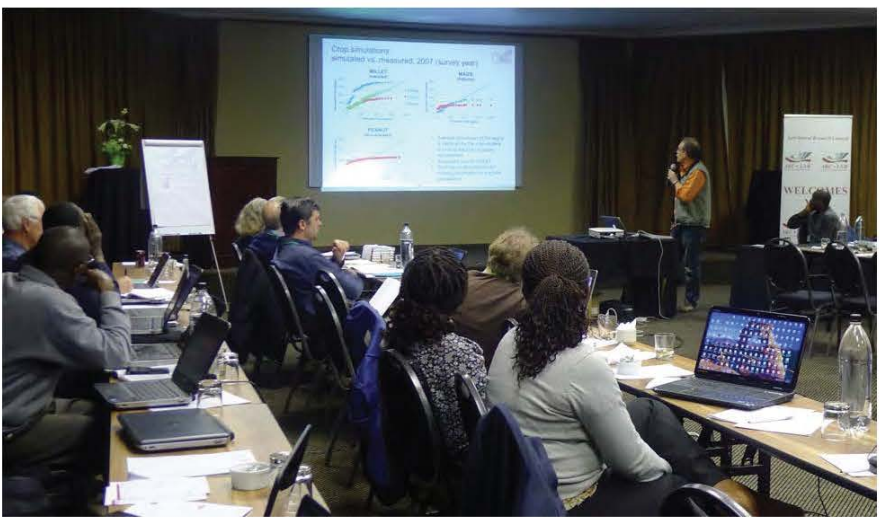
RAPS will be end in August in Ethiopia, Tanzania and Uganda. Country regional reports will be ready end of December where team will also prepare for publications.

For stakeholder engagement, these are divided into direct users and intermediaries including media. By end of August, team will have a full list of stakeholders in each country and at around December, and with some more results, hold national stakeholder engagement. At end of year, we will present a more comprehensive set of results to stakeholders in ASARECA forum.

SAAMIP presentation at plenary

Climate data show that annual temperature will increase over the baseline while precipitation decreases or decreases depending on the GCM used. The team showed also the presentation and interpretation of results as they understand, a great improvement compared to in day 1. For the homestretch, the team will work with 2 models (DSSAT and ApSIM) and work in 5 countries. Work was shared among the country teams specifying the specific region and crops to be analyzed, whether survey data are matched or unmatched etc. The current thinking on adaptation was shown indicating that commercial farmers may have variety change, irrigation, change of crop, while small-scale farmers also may have variety change, optimization of inputs and change to high value crops. Team targets to finish model simulations latest December 2013. The team has one site per country and there is a crop modeler and an economist in each country to ensure that modeling in each country will continue in parallel.

In discussions, Alex Ruane suggested that teams share the scripts and tools that they develop, including for visualizations, so coordination team can share around.



Day five plenary presentation.

CLIP presentation at plenary

CLIP observed increases in temperature of about 2-3°c from all GCMs as compared to the baseline for the example site, consistent with SAAMIIP. Also, DSSAT overestimated stover in the calibration dataset. In the Home stretch, team will focus on Zimbabwe (complete run), Malawi (climate and crops, limited economics), Botswana and SA (crop and climate). The adaptation package that the team proposes to use was shown including use of long-duration variety, ISFM (combination of organics and inorganics), different crop mixes, decreased animal mortality e.t.c. There are already long-duration varieties in ApSIM that could be used initially. Ideas for extension of AgMIP phase were also provided including effect of temperature on livestock, testing of heat tolerant varieties as asked by stakeholders from Zimbabwe.

Model development and model use capacity is partial. CLIP has capacity for ApSIM but not for DSSAT. They suggested that conversions be made to convert genetic coefficients from one to another. ApSIM requires some coefficient not needed in DSSAT and similarly the opposite direction. Crop modeling global team needs more information on the challenges modellers in RRTs are facing. It is important to understand the differences in the different model results so that it is no longer a black box. i.e., don't forget to take time and interpret the results from the modeling that you are getting.

CIWARA presentation at plenary

CIWARA showed some results from climate, crop and economics side and also the level of completion in the different countries. They also showed what they will achieve by February 2014. The team has reduced from 10 to 5 the number of sites to cover in this phase of the project. On stakeholder engagement, the team identified key questions on this. It also presented what it would want to do in an extension phase of the project that include improvement of agricultural statistics, further develop capacity in AgMIP core skills, and intensify stakeholder engagement among others.

KEMIC presentation at plenary

There is need to define data in AgMIP into Platinum, Gold, silver e.t.c. and starting with the how this will be done. Coordination (RCT) can help to define this and the criteria. Data is very important and we need to load it to the ftp sites. RCT can help to upload data if RRTs have a problem. RCT can coordinate for the publication of data into the AgMIP databases for access to wider groups. Data should be quality controlled and provided with metadata. There will be a way very soon for scientists to publish their data. We do not however want to violate copyright issues.

Agenda for PI call next time should be data publication. We need guidelines on how the data are stored. Another question is on the public release standards so that those putting in data have understanding, i.e., data sharing policy.

Final highlights and feedback from leadership

Alex Ruane presented highlights on C3MP and invited workshop participants to register. Jon provided some guidelines on development of adaptation packages/cases. The materials will put into a short document. The approach should be technically and economically feasible. This process should be seen as an extension of raps work, therefore team work is needed. Also, it helps to have a narrative description of what motivates the adaptation. The adaptation package should consist of crop models

(variety, fertilization, water) and TOA-MD (production systems component, economics/policy components).

AgMIP leadership noted that we did not so much discuss adaptation and that what we are doing here is new and requires inter-disciplinary approach with all disciplines working together. Also the different models differ and therefore model improvement is very important. Where are improvements needed, where do they fail as opposed to what is required. As you document and interpret the results relative to your understanding and data, try to document what you are learning in this first phase. Some could be model improvement or just methodological in terms of the assumptions we make. Document any improvements done as well. We will update you on future plans including extension. In interpretation, teamwork is needed and it will be nice to document where this is done.

We are trying to put together a database and we will develop guidelines. Let us follow the current trends in agricultural data publishing. Let's work together on publishing our datasets.

Finally, Cynthia Rosenzweig took participants through the checklist of workshop goals. We have demonstrated that the fast track check is excellent. Each team developed clear and realistic work-plans for the remaining project period, which required clear thinking of what is possible. The plan for the homestretch (actual analysis across the sites) has been well done. PIs were appreciated for providing abstracts for the draft manuscripts for the second handbook on integrated regional assessments with AgMIP. A lot of progress was made with stakeholder interactions, which was really great.

Appendix 1. Workshop program

Overall workshop goals:

1. Demonstrate the accurate completion of the mid-term workshop checklist
2. Work together on multidisciplinary analysis of simulation results
3. Ensure that each team has clear work plan to achieve full project goals
4. Work on post-fast-track integrated assessments, analyses, and publications
5. Develop plan for dissemination of AgMIP results to inform stakeholder actions

Day 1 - Monday, 15 July

Goals:	1) Provide overview on "state of AgMIP" to the teams and stakeholders
	2) Assess overall progress of teams and disciplinary leaders to date
	3) Conduct facilitated discussion with Stakeholders
08:00	**Registration**
08:30	Welcome and Introductions, Workshop goals – J Jones
09:00	Official opening speech (Dr Shadrack Moephuli, CEO-ARC)
09:20	State of AgMIP – C Rosenzweig
10:00	Regional Research Team (RRT) presentations based upon Mid-term Workshop Report-in Template
	SAAMIP
	CLIP
10:40	**Tea/Coffee Break**
11:10	Continue Regional Project Presentations
	East Africa
	CIWARA
	Regional Coordination Team (CRT)
12:10	Discussion
12:30	**Workshop Photo, Lunch**

14:00 Charge to afternoon breakouts – P Craufurd

14:15 Climate, Crops, Economic, and Coordination Team breakouts

- RRT members breakout by expertise
- Present Mid-term checklist results in detail
- Determine methodological challenges for workshop
- CRT meets with stakeholders

15:30 **Working Tea/Coffee Refreshment**

17:00 Facilitated discussion with stakeholder inputs – C Rosenzweig

18:00 **Adjourn for the day**

18:30 **Reception**

Day 2 – Tuesday, 16 July

Goals: 1) RRT interactions with stakeholders

2) CRT facilitates stakeholder interactions and learning among groups

3) Leaders review and evaluate progress of each team

08:30 Plenary Session - Review workshop goals, day's goals – J Jones

08:45 Charge to RRT/CRT breakout groups – P Craufurd

09:00 RRTs meet with stakeholders from region to discuss progress, aims, and potential outcomes. Each team will also have a 45 minute technical session to meet with the AgMIP leaders for feedback and guidance on next steps (this technical session will not include stakeholders). CRT members disburse among RRTs to learn more about each regional project and its stakeholder objectives.

09:00 SAAMIP visits Leaders

09:45 CLIP visits Leaders

10:30 **Working Coffee/Tea Refreshment**

10:45 East Africa visits Leaders

11:30 CIWARA visits Leaders

12:15	CRT visits Leaders
13:00	**Lunch**
14:00	Plenary Session – Charge to RRT Breakouts – P Craufurd
14:15	RRT Breakouts – methodological challenges and multidisciplinary assessment
15:30	**Working Coffee/Tea Refreshment**
17:30	Plenary - Report Back - Review next day plans – C Rosenzweig & J Jones
18:00	**Adjourn for the day**

Day 3 – Wednesday, 17 July

Goals:	Continue RRT & CRT work; Field Trip (Optional)
08:30	Plenary Session – Goals for Day 3 – C Rosenzweig
08:45	Charge to RRT Breakouts – P Craufurd
09:00	RRT Breakouts
10:30	**Working Coffee/Tea Refreshment**
13:00	**Lunch**
14:00	**Field Trip to farms near Hartbeeespoort Dam (return at 18:30)**
18:30	**Return**

Day 4 – Thursday, 18 July

Goals:	Continue RRT and CRT work, design work priorities for remainder of project.
08:30	Plenary Session – Results from Day 3, goals for Day 4 – J Jones
08:45	Charge to Team Breakouts – P Craufurd
09:00	Team Breakouts – Leaders Breakout & Float as needed
10:30	**Working Coffee/Tea Refreshment**
12.00	RRT PIs join AgMIP leaders at noon to discuss remaining work.
13:00	**Lunch**

14:30	Plenary – Research goals for remainder of Project – A Ruane
15:05	Plenary – Data Plan – C Porter
15:15	**Working Coffee/Tea Refreshment**
15:30	RRT Breakouts – Organize workshop reports and assess priorities for the remainder of the project
17:00	Plenary - Report Back - Review next day plans – C Rosenzweig & J Jones
17:30	The Coordinated Climate Crop Modeling Project (Optional) – A Ruane
18:30	**Adjourn for the day**

Day 5 Friday, 19 July

Goals:	Teams and Leadership finalize work plans and workshop reports
08:30	Plenary - Goals for Day 5 – C Rosenzweig & J Jones
08:45	RRT Breakouts & Leaders Breakout – Finalize workshop presentations and create work plan for remainder of project including potential publications
10:15	**Working Coffee/Tea Refreshment**
10:45	**Plenary** – RRT & CRT Reports – 45 minutes each – status and plans
10:45	SAAMIP
11:30	CLIP
12:15	East Africa
13:00	**Lunch**
14:00	**Continue Plenary**
14:00	CIWARA
14:45	Coordination Team
15:30	**Feedback from leadership, Discussion**
17:00	**Adjourn**

Appendix 2. Participant list for the SSA Midterm workshop in Pretoria

No.	Name	Organization	Country	Email Address
	AgMIP Leadership Group+ resource Persons			
1	Alexander Clarke Ruane	NASA GISS	USA	alexander.c.ruane@nasa.gov
2	Carolyn Zehnder Mutter	Columbia University/Earth Institute	USA	czm2001@columbia.edu
3	Cheryl Porter	University of Florida	USA	cporter@ufl.edu
4	Cynthia Elise Rosenzweig	University of Columbia	USA	crr2@columbia.edu
5	Ioannis N. Athanasiadis	Democritus University of Thrace	Greece	ioannis@athanasiadis.info
6	John M. Antle	Oregon State University	USA	John.Antle@oregonstate.edu
7	Jim Jones	University of Florida	USA	jimj@ufl.edu
8	Shari Lynn Lifson	Columbia University/Earth Institute	USA	sll2158@columbia.edu
9	Katrien Descheemaeker	Wageningen University, Wageningen	Netherlands	katrien.descheemaeker@wur.nl
10	Davide Cammarano	University of Florida	USA	davide.cammarano@ufl.edu
11	Kenneth J. Boote	University of Florida	USA	kjboote@ufl.edu
12	Peter Craufurd	ICRISAT-Patancheru	India	P.Craufurd@cgiar.org
13	Jon Lizaso	Universidad Politecnica de Madrid	SPAIN	jlizaso@ufl.edu
14	Roberto Valdivia	Oregon State University	USA	roberto.valdivia@oregonstate.edu
	AgMIP KEMIC Group			
1	Dilys S. MacCarthy	Agriculture Research Center, University of Ghana	Ghana	kpongor@yahoo.com
2	Job Kihara	CIAT, Kenya	Kenya	J.Kihara@cgiar.org
3	Andre Bationo	AGRA, Accra Ghana	Ghana	ABationo@agra.org
4	Charles Vanya	Dept of Climate Change & Meteorological Services, Blantyre	Malawi	charles.vanya@yahoo.com
5	Juliet Ogola	CIAT, Kenya	Kenya	j.ogola@cgiar.org
6	Jonathan Hickman	Columbia University/Earth Institute	USA	jhickman@gmail.com
	AgMIP CLIP Group			
1	Patricia Masikati	ICRISAT - Bulawayo	Zimbabwe	p.masikate@cgiar.org
2	Arthur Chibwana Gama	Bunda College of Agriculture	Malawi	arthurchibwana@gmail.com
3	Lieven Claessens	ICRISAT - Nairobi	Kenya	L.Claessens@cgiar.org
4	Sebastao Famba	Universidad Eduardo Mondlane, Maputo	Mozambique	sifamba@uem.mz

5	Chris Lennard	University of Cape Town		lennard@csag.uct.ac.za
6	Sabine Homann Harannkeethi	ICRISAT - Bulawayo	Zimbabwe	S.Homann@cgiar.org
	AgMIP CIWARA Project Group			
1	Pierre C. Sibiry Traore	AgMIP West Africa Region, Head, GIS ICRISAT - Bamako	Mali	p.s.traore@CGIAR.ORG
2	Samuel G.K. Adiku	AgMIP West Africa Region, University of Ghana	Ghana	s_adiku@hotmail.com
3	Bright Salah Freduah	SIREC, University of Ghana, Legon	Ghana	kobebryt@hotmail.com
4	Madina Diancoumba	University of Ghana, Legon	Ghana	madina.diancoumba@yahoo.fr
5	Seydou B. Traore	AGRHYMERT, Niamey	Niger	s.traore@agrhymet.ne
6	Agali Alhassane	AGRHYMERT, Niamey	Niger	alhassaneagali@yahoo.fr
7	Dougbedji Fatondji	ICRISAT Sahelian Center, Niamey	Niger	D.Fatondji@cgiar.org
8	Ibrahima Hathie	Initiative Prospective Agricole et Rurale, Dakar	Senegal	ihathie@yahoo.com
9	Joseph Amikuzuno	University of Development Studies, Tamale	Ghana	amikj26@yahoo.com
10	Moussa Sanon	INERA, Ouagadougou	Burkina Faso	moussanon@hotmail.com
11	Tiganadaba Lodoun	INERA, Ouagadougou	Burkina Faso	tiganadaba@yahoo.fr
12	Myriam Adam	CIRAD - Departement Systemes Biologiques (BIOS)	France	myriam.adam@cirad.fr
	AgMIP EA Project Group			
1	KPC Rao	ICRISAT - Nairobi	Kenya	K.P.Rao@cgiar.org
2	Benson M. Wafula	Agroclimatologist - KARI-Embu	Kenya	Bensonwafula@gmail.com
3	Sridhar Gummadi	SPS, ICRISAT-Ethiopia, Addis Ababa	Ethiopia	S.Gummadi@cgiar.org
4	Richard M. Mulwa	University of Nairobi	Kenya	richard.mulwa@yahoo.com
5	Mary Kilavi	Kenya Meteorological Department	Kenya	mkilavi@meteo.go.ke
6	Carolyne Wafula	Kenya Agricultural Research Institute	Kenya	ckhalayi@yahoo.com
7	Araya Alemie Berhe	Mekelle University	Ethiopia	arayaalemie@gmail.com
8	Robel Takele	Ethiopian Institute of Agricultural Research (EIAR)	Ethiopia	takelerobel@gmail.com
9	Kebede Manjur Gebru	Mekelle University	Ethiopia	solomonmanjur@gmail.com
10	Jacqueline Bonabana Wabbi	Makerere University, Kampala	Uganda	jbexim@gmail.com
11	Omari Mzirai	AgMIP Crop Group, IRDP, Dodoma	Tanzania	imzirai@gmail.com
12	Peter Nicky Mlonganile	Meteorological Agency (TMA), Dar-es-Salaam	Tanzania	pmlonganile@yahoo.co.uk

	AgMIP SAAMIIP Project Group			
1	Yacob Beletse	ARC Potchefstroom	South Africa	BeletseY@arc.agric.za
2	Olivier Crespo	University of Cape Town	South Africa	olivier.crespo@csag.uct.ac.za
3	Wiltrud Durand	ARC Grain Crops Institute, Potchefstroom	South Africa	DurandW@arc.agric.za
4	Charles Nhemachena	Human Science Research Council, Pretoria	South Africa	CNhemachena@hsrc.ac.za
5	Mduduzi Sunshine Gamedze	Swaziland, University of Free State, Bloemfontein	South Africa	gamedze@gmail.com
6	Mogos Teweldemedhin	Polytechnic of Namibia, Windhoek	Namibia	tmogos@polytechnic.edu.na
7	Patrick Gwimbi	National University of Lesotho	Lesotho	pgwimbi@yahoo.com
8	Zinyengere Nkulumo	University of Cape Town	South Africa	nkulumo@csag.uct.ac.za
9	Thembeka Mpuisang	Botswana College of Agriculture	Botswana	tmpuisan@bca.bw
10	Sue Walker	Crops for Future Research Centre, Cheras	Malaysia	sue.walker@cffresearch.org
11	Weldemichael Tesfuhuney	University of Free State, Bloemfontein	South Africa	weldit@yahoo.com
12	Jonas Siyanda	Human Sciences Research Council	South Africa	SJonas@hsrc.ac.za
13	Pontsho Montle Bonolo	Polytechnic of Namibia, Windhoek	Namibia	bpmontle@gmail.com
14	Girma Hiywot	University of Pretoria, Pretoria	South Africa	hiywotmenker@yahoo.com
	Stakeholders			
1	Stephen King'uyu	Ag. Deputy Director (Adaptation & Mitigation), Climate Change Secretariat	Kenya	king_uyu@yahoo.com
2	Dumisani M. Nyoni	Provincial Director, Dept of Agric Techn & Extension Services, Bulawayo	Zimbabwe	dumienyoni@yahoo.com
3	Olaotswe Kgosikoma	PARO, Department of Agricultural Research, Gaborone	Botswana	mfana450@yahoo.com
4	Luciano Rafael Majone	DPA, Chimoio	Mozambique	luciano60225@yahoo.com.br
5	Timothy Gondwe	Associate Professor, Lilongwe University, Lilongwe	Malawi	tlmgondwe@yahoo.com
6	Makananisi Funzani	Climate Chabge Analyst, Dept of Agric Forestry & Fisheries, Pretoria	South Africa	FunzaniM@daff.gov.za

Appendix 3. Stakeholder biographies

Stephen Mutua KING'UYU, Ag Deputy Director – Adaptation and Mitigation at the National Climate Change Secretariat, Ministry of Environment, Water & Natural Resources, Kenya. Current responsibilities include the domestication of conventions and protocols related to climate change adaptation and mitigation and coordination of the relevant national policy processes. KING'UYU coordinated the preparation of Kenya's National Climate Change Action Plan (NCCAP), which is a policy instrument to help address climate change across the different sectors of the economy.

Dumisani Mbikwa Nyoni, Provincial Agricultural Extension officer in the Department of Agricultural Technical and Extension services, Zimbabwe. Nyoni's current focus is to promote conservation agriculture to address climate change challenges, develop and strengthen input-output value chains to stimulate agricultural production through linking farmers to markets, farmer training on climate change issues, design agricultural project interventions that address challenges associated with climate change, develop use of ICT in agricultural extension, and strengthen research-extension farmer linkages.

Olaotswe Kgosikoma currently works for the Department of Agricultural Research, Botswana, focusing on sustainable use of range and pasture resources. His research interests are interactions between livestock species, rangeland conditions, and fodder crops and climate change, with the goal of assisting farmers to adapt and mitigate adverse impacts of climate change. Kgosikoma is also a member of Botswana National Committee on Climate Change, responsible for advising government and raising community awareness of climate related issues.

Luciano Rafael Majone, Provincial Directorate of Agriculture of Manica, Mozambique, involved in the planning and monitoring of the agricultural sector.

Timothy Gondwe (PhD), Associate Professor of Animal Breeding and Deputy Dean of Agriculture at Bunda College of Agriculture (BCA), Lilongwe University of Agriculture and Natural Resources (LUANAR), Malawi. Gondwe teaches Applied Animal Breeding, Advanced Quantitative Genetics, Biometry and Computing (msc level), Biostatistics and Research Methods (phd Aquaculture), Village and Commercial Poultry Production, Livestock Production Systems, Undergraduate Animal Breeding and Genetics, and design and analyses of students' experiments and surveys using SAS, Genstat and SPSS Statistical Packages. Dr Gondwe has been engaged in designing and training of government and NGO food security projects on harmonization of monitoring and evaluation system for projects in Malawi.

Makananisi Funzani, Climate Change Analyst, Department of Agriculture Forestry & Fisheries, Pretoria, South Africa. Previously Ms. Funzani worked as an Agriculture Resource Technician where she focused on the land care program and communicating disaster and climate change management to farmers.

Appendix 4. FAQs

AgMIP RRTs: The Home Stretch

Climate Team FAQs

1) Which specific climate scenarios are required for core question simulation sets:

- RCP8.5
- Mid-Century
- Delta Scenario ('XA.AgMIP' in Climate Codes)
- 5 GCMs [CCSM4 (E), GFDL-ESM2M (I), HadGEM2-ES (K), MIROC5 (O), MPI-ESM-MR (R)]
- All farms

2) Why do we all use the same 5 GCMs?

- We are interested in consistency among regions and therefore require the same 5 GCMs to be used in all locations in Sub-Saharan Africa and South Asia.
- The 5 GCMs above were selected for their:
  - Widely used in recent assessments
  - Rigor of processes and resolution
  - Performance in monsoon regions

3) Will we assess the broader uncertainty of climate change projections?

- Yes, for 2 crop models, RCP8.5, Mid-Century

3a) Mean Changes Only

- 20 GCMs run only through crop/livestock model (no TOA runs)
- Delta Scenarios ('XA.AgMIP' in Climate Codes)
- 1 field: Best calibrated crop/livestock model location

3b) Mean and Variability Changes

- 20 GCMs run only through crop/livestock model (no TOA runs)
- Mean and Variability Scenarios ('XF.AgMIP' in Climate Codes)
- 1 field: Best calibrated crop/livestock model location

Crop/Livestock Model Team FAQs

1) How many crop/livestock models are needed for core question simulation sets?

- 2 crop models
- 1 livestock model (CLIPs)

2) How many crops/livestock are required for a given production system?

- At least one

3) What are the crop/livestock model components of the adaptation package?

- Regional Research Teams devise combination of adaptations represented in crop/livestock model parameters

Economic Model Team FAQs

1) Will we use a RAP for core question #1?

- No

2) What RAP will we use in core questions #2 and #3?

- Regional Research Teams are developing R1: Current Trends Continue

3) How will RAPs incorporate global and regional drivers?

- Begin with national-level drivers from global economic model
- Adjust to regional drivers

Information Technologies Team FAQs

1) How can we organize and execute large number of simulations?

- Core question crop/livestock runs at all farms: DOME
- Climate sensitivity runs at one location: Take experiment file (e.g., from QuadUI) for location and add 40 fields that each have different climate

2) Where will inputs, outputs, and products be archived?

- Utilize AgMIP data flow for Regional Integrated Assessments

Appendix 5. Mid-Term Workshop Checklist

This document provides a checklist that will help each team determine whether they are on track to produce all needed elements for the full examination of an integrated assessment at the July Mid-term Workshop. We will go through the entire integrated assessment for this single scenario in your integrated assessment region at the workshop, and then will develop a clear plan for the full assessment(s) going forward from the Midterm workshop to the end of the project (which will include additional elements). Details of these files and the associated methodologies are provided in the AgMIP Integrated Assessment Handbook (available at http://www.agmip.org/wp-content/uploads/2013/05/AgMIP-Regional-Research-Team-Handbook-v4.1.pdf)

Checklist – Climate Time Series Files

The .AgMIP file name is shown here to indicate that these files will need to be consistently formatted following the example in the AgMERRA dataset, and the naming convention detailed in the handbook also provides information about the specific files created. These will enable the full suite of crop modeling runs and agro-climatic analyses for the project.

Using New York City (USNY) as an example:

* **1.1 obtain AgMERRA estimated climate series for main weather location**
  first step: send an email to Alex (alexander.c.ruane@nasa.gov) with location's latitude, longitude, elevation, full name, and a 4-character code (e.g., USNY)
  file: **USNY0QXX.AgMIP**

* **1.2 combine with observations and quality control main weather station**
  first step: collect observations and calculate biases of AgMERRA time series. Fill in gaps using methodologies described in Section 4 of AgMIP Regional Integrated Assessment Handbook to achieve 1980-2010 daily file with all AgMIP variables.
  file: **USNY0XXX.AgMIP**

* **1.3 create CMIP5 GCM delta scenarios for Mid-Century (2040-2069) RCP8.5 using the CCSM4 global climate model scenario**
  first step: download CMIP5 datasets (meantasmax, meantasmin, meanpr, and lat/lon files) and Matlab/R scripts package
  file: **USNYIEXA.AgMIP**

Check List – Crop Modeling for Integrated Assessment

□ **2.1** Document calibration of selected cultivar used (indicate experimental site, number of years, and type of experimental data used for calibration). Provide the cultivar genetic coefficients and evidence of calibration (simulated and observed anthesis and maturity with statistics, and graphical time-series if done). Provide model-ready input files.

□ **2.2** Provide completed template spreadsheet (Survey_Data_Import file) of entered field survey data that includes all farmer fields.

* **2.3** Document source and identity of weather data used for farm survey simulations (including the weather used for simulating farm survey seasons, as well as the historical baseline weather (USNY0XXX.AgMIP), and the future climate scenarios (e.g., USNYIEFA.AgMIP). Also confirm that your weather files follow the AgMIP-scripting method and that the future climate scenario is for the correct time-slice and RCP).

□ **2.4** Document source of soil profile information and provide soil profiles (either as separate page on the template spreadsheet, or as separate soil profile that can be viewed).

□ **2.5** Provide Field Overlay files (DOME or DOMES) used to fill in missing information relative to the farm survey simulations. For example, that will give evidence for setting initial soil water, initial soil nitrate and ammonium, assumption for initial crop residue, stable soil C pool fraction, etc. This may require a short amount of explanatory text.

□ **2.6** Provide the ACMO file with the simulated crop yield outputs for the matched farm yield survey fields, with explanation. Discuss causes for outliers in observed and simulated farm yields, *but as requested by economists, do not make any bias adjustments.*

□ **2.7** Provide the ACMO file of successful 30-year simulations for baseline weather, for all farms (30 years per farm, show simulated yields for individual years, no averaging). Also provide Seasonal Strategy file (DOME) to provide sowing date rules and other assumed management information.

□ **2.8** Provide the ACMO file of successful 30 year simulations for the appropriate identified climate scenario, for all farms (30 years per farm, show simulated yields for individual years, no averaging). This is for historical management without RAPS. This will require an additional Seasonal_Strategy file (DOME) to provide sowing date rules and other assumptions.

□ **2.9** For adaptation simulations, provide Seasonal_Strategy file (DOME) with RAPS adaptations, sowing rules, and assumptions, along with ACMO file of 30 year simulations for climate change scenario with adaptation, for all farms (30 years per farm, show simulated yields for individual years, no averaging).

□ **2.10** Provide evidence of interactions with economists on your team to confirm their understanding of the files and how to interpret crop modeling results, with yield distributions associated across farms in the matched survey case, and yield distributions associated with multiple weather years per individual farm.

Check List – Economics Team: TOA-MD Modeling

This checklist is to be used by RRT's economists for TOA-MD data preparation, model setup and results review. This checklist should be used for each scenario that is being modeled (i.e. Fast track, and adaptation scenarios).

DATA: Review data received from crop modelers and economic survey data

□ **3.1** Make sure you received data from crop modelers in ACMO format

□ **3.2** Check actual data for outliers, make histograms

□ **3.3** Check simulated yields distributions

- □ **3.4** Correctly estimate relative yields and predicted future yields - Follow instructions provided on the updated Appendix 1 of the Handbook v4.1
- □ **3.5** Stratification: decide if stratification is needed/possible
- □ **3.6** Calculate statistics and double check they are correctly estimated (check predicted/modeled standard deviations, CVs) - Check again for outliers, strange values, etc
- □ **3.7** Make sure input parameters are consistent with scenario being modeled
- □ **3.8** Estimate and make sure RHO12 (correlation between returns in systems 1 and 2) makes sense
- □ **3.9** If needed, estimate and check values for correlations between returns to activities within systems (e.g. RHOC1, and RHOC2 for crops).
- □ **3.10** Use DATA and STUDY sheets to document the scenario that is being modeled.

MODEL Setup: Review key TOA-MD parameters and output data

- □ **3.11** Select the appropriate value for Do_Climate (Setup sheet)
- □ **3.12** Check units and select appropriate value for C_UNITS, L_UNITS, P_UNITS
- □ **3.13** Check units for CVs
- □ **3.14** Check STD_C, STD_L, STD_P: Standard deviation of net returns
- □ **3.15** Check activity Weights
- □ **3.16** Check fixed costs (are they needed?, enter correct values and check values for T1, T2 ,R)
- □ **3.17** Review all sheets making sure all the values are correct, consistent and in the correct places

Model Results:

- □ **3.18** Check output sheets for consistency
- □ **3.19** Check range of tradeoff points
- □ **3.20 Interpretation**: Review results to make sure they are consistent with economic theory and TOA-MD economic/statistical properties

Check List – Technical Stakeholder Engagement

The workshop includes engagement of at least one technical stakeholder (TS) per team for the first 1.5 days of sessions. This is owing to 1) A requirement by the funder (UK/DFID) to engage stakeholders broadly and across time; 2) Recognition that TS engagement is part of the underway work; and, 3) To ensure teams are not too far down the product line for a country before taking into consideration the likely areas of influence or need. The TS interactions should actually help to shape the work. Below we provide some criteria to help you in your selection of suitable TS. Teams should plan to have no fewer than two TS participating. AgMIP (HQ) will fund one, with the team funding the other.

- □ **4.1** TS works in one of the countries in your region
- □ **4.2** TS contributes technical expertise at a sub-national or national level

□ **4.3** TS would likely benefit from exposure to the fuller AgMIP SSA representation

□ **4.4** TS would likely engage in the technical discussion session on the afternoon of Day 1

□ **4.5** TS would likely be interested and able to explore some RAPS-like work with your team in the morning of Day 2.

Team PIs will reach out to TS and provide information and full contact information also the Coordinating Research Team PI (Job or Dileep) with a copy also to agmip@columbia edu. AgMIP HQ will fund one TS for each team.

Appendix 6. FTP site naming conventions

1. CLIMATE

1.1 The merged historical period file (file name format: USNY0XXX.AgMIP). This come from historical observations merged with the MERRA-based data (bcMERRA is the same as AgMERRA), and should be complete from 1980-2010 with all variables and should not have any major outliers or physical discontinuities (e.g., Tmax < Tmin).

1.2 The historical period files for each farm in the region (e.g., if we had 12 farms around New York, we would have files name formats NY010XXX.AgMIP –> NY120XXX.AgMIP). These come from the agmip_farm2climate R scripts and the WorldClim data.

1.3 An example of the future climate data (from agmip_simple_delta.R and agmip_simple2full.R) from one GCM (use CCSM4 if you are looking for a first one to upload). File name format: NY01GEXA.AgMIP --> NY12GEXA.AgMIP

2. CROP

2.1. Crop model files for DSSAT (or XML for APSIM) documenting cultivar genetic coefficients used (provide experimental data for site used for calibration).

File name format: Files X, A, T, *.SOL, *.WTH, and *.CUL used for DSSAT models (in the standard DSSAT naming conventions), and the XML files for APSIM (with corresponding cultivar, management, soils, weather information in the APSIM naming conventions).

2.2. Field survey data entered. File name format: Survey_Data_Import-Region-Crop.csv

2.3. Field Overlay files (DOMES) used to fill in missing information for farm survey simulations. File name format: Field_Overlay_Region-Crop-Model.csv [Note: provide all (multiple) DOMES associated with the above Survey_Data_Import-Region-Crop.csv files]

For all the below ACMO files please use the following naming format:

ACMO-region-stratum-ClimID-RAPId-MgmtID-model.csv

For example

ACMO-Machakos-1-0XFX-0-0-DSSAT.csv for baseline,

ACMO-Machakos-1-MTFA-3-2-APSIM.csv for future conditions.

2.4. ACMO file with simulated crop yield outputs for the matched farm yield survey fields.

2.5. ACMO file of 30-year simulations for baseline weather, for all farms, with Seasonal Strategy file (DOME) for sowing rules and other assumed management information.

2.6. ACMO file of 30-year simulations for climate scenario, for all farms, with Seasonal Strategy file (DOME) for sowing rules and other assumed management information.

2.7. ACMO file of 30 year simulations for climate scenario with adaptation, with Seasonal_Strategy file (DOME) with RAPS adaptations, sowing rules, and assumptions.

3. ECONOMIC

3.1 Modeling:

- TOA-MD Input files (excel files). Use the TOA-MD data file name format: MD4data_YYYYY.xls (YYYY:Project identifier: team, region and scenario description)

- TOA-MD Output files (excel files). Use this TOA-MD output File name format: MD5_YYYY.xls

3.2 Reporting: use previously provided template to report results:

- RRTs FT-AD Report (PowerPoint and Excel files). Use the file name format of the templates provided and add the project identifier: YYYY_RRTs FT-AD Report.PPt and YYYY_RRTs FT-AD.xls

3.3 RAPs:

- DevRAP Matrix Use the DevRAP filename and add the Project identifier: YYYY_DevRAP.xls

- RAPs Documentation (based on template we distributed). Use this File name format: YYYY_RAPS Documentation.doc

- RAPs Presentation – Summary of RAPs narratives. Use this File name format: YYYY_RAPs Summary.PPT

Appendix 4

This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

SOUTH ASIA MID-TERM WORKSHOP REPORT

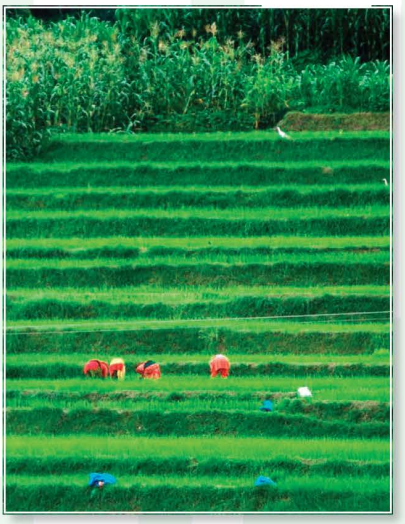
REGIONAL INTEGRATED ASSESSMENTS

JULY 22-26, 2013
KATHMANDU, NEPAL

ICRISAT

UKaid from the British people

USDA



Contents

Introduction 2
Mission and goals 2
Objectives 2
Summary 2
Sessions – DAY 1 3
Welcome and Introductions, Workshop goals 3
State of AgMIP 3
Pakistan 4
Indo – Gangetic Basin 6
Sri Lanka 9
Southern India 11
South Asia Regional Coordination Team 12
Sessions – DAY 5 14
Pakistan 14
Indo Gangetic Basin 15
Sri Lanka 17
Southern India 18
South Asia Regional Coordination Team 20
Breakout Sessions 22
Conclusion 23
Annexure 1: Agenda 24
Annexure 2: Participants 28
Annexure 3: Presentations Website 38
Annexure 4: FAQs 39
Annexure 5: Mid-Term Workshop Checklist 41
Annexure 6: FTP site naming conventions 44

Acknowledgements

This workshop was made possible by support from UKAID. Institutional support from CIMMYT and ICRISAT was also appreciated. Organizational support was provided by V V Sumanth Kumar and D Murhty. Workshop report was prepared by V V Sumanth Kumar and Drs Subash, D Murhty and Nedumaran with oversight from G Dileepkumar with additional inputs from S. Lifson and C. Mutter. Thank you to AgMIP PIs and Leadership for their contributions to the program and planning and execution of the Workshop. Thank you also to the regional stakeholders for their generous time and participation. We are also thankful to AgMIP leadership team for providing valuable inputs.

Introduction

The Agricultural Model Intercomparison and Improvement Project (AgMIP) is a major international effort to improve the state of global agricultural modeling and to understand climate impacts on the agricultural sector (www.agmip.org). AgMIP connects research communities for climate science, crop models, and agricultural economics models via a transdisciplinary framework with an emphasis on developing the information technology tools required for probabilistic projections of current and future climate impacts.

AgMIP has a Two-Track Science Approach – one is Model Intercomparison and Improvement and the other is Climate Change Multi-Model Assessment. Both tracks are facilitated by a series of regional workshops held in each AgMIP region over a 3-year period of time as well as by global studies and workshops that focus on particular crops and on global analyses. Participants at the regional workshops conduct analyses at field-to-regional scales and include crops and economic model intercomparisons and improvement activities, as well as simulations with guided climate sensitivity tests and climate change scenarios.

Mission and goals

The mission and goals of AgMIP are to improve substantially the characterization of risk of hunger and world food security affected due to climate change and to enhance adaptation capacity in both developing and developed countries.

Objectives

- Incorporate state-of-the-art climate products as well as crop and agricultural trade model improvements in coordinated regional and global assessments of future climate impacts
- Include multiple models, scenarios, locations, crops and participants to explore uncertainty and impact of data and methodological choices
- Collaborate with regional experts in agronomy, economics, and climate to build strong basis for applied simulations addressing key climate-related questions
- Improve scientific and adaptive capacity for major agricultural regions in the developing and developed world
- Develop framework to identify and prioritize adaptation strategies
- Link to key ongoing efforts with partners including,
    - CCAFS, Global Futures, MOSAICC, Yield Gap Analysis, SERVIR, MACSUR
    - National Research Programs, National Adaptation Plans, IPCC, ISI-MIP

Summary

The AgMIP South Asia Mid-term Workshop was conducted to bring together participants from the Regional Research Teams and Coordinating Team with AgMIP Leadership to:

- Demonstrate the full and accurate completion of the fast-track;
- Ensure that each team has a clear work plan to achieve full project goals, including the engagement of technical stakeholders;
- Work on post-fast-track integrated assessments and analyses; and,
- Develop plan for dissemination of AgMIP results to inform stakeholder actions.

Sessions – DAY 1

Welcome and Introductions, Workshop goals

The workshop began with Jim Jones giving a snapshot of the whole program for the week. The workshop consisted of scientists from all four spheres. There were economists, crop modellers, climate scientists, soil scientists, and agronomists. The workshop was supposed to have a number of breakout sessions to work on the fast-track work, prepare presentations, and harmonize those presentations so that the results can be compared across the region.

Jim Jones

State of AgMIP

It was also announced during the session that the whole project will have a major publication apart from the other publications and all the work will be brought together in the form of a book which is a part of the series "A Handbook of climate change and agro eco systems" and each of the regional teams will have their individual chapters.

Another task to be performed by the teams was to prepare a poster of the regional project which will be presented at the global annual workshop of AgMIP, which will be held in October in New York. The prinicipal investigators were invited to present the regional projects in the AgMIP symposium at the annual society of agronomy annual meetings to be held at Tampa, Florida, as well as a presentation on the regional projects, results, interpretation, and analysis of the results at the American Socity of Agronomy (ASA) meetings. They were also requested to bring along a draft of the respective chapter, in order to help in the completion of the book by the next ASA meeting one year later.

AgMIP has a Two-Track Science Approach:-

1. Model improvement and Intercomparison
2. Climate Change Multi-Model Assessment

It was mentioned that a model includes not only the biophysical modelling but also the economic modelling; in order to understand how changing climate, climate extremes, and climate variability will affect agriculture, we have to work together across these disciplines to have the full picture. AgMIP works both at the regional and global scales.The speaker also talked about cross cutting themes like Uncertainty, Aggregation, and Scaling at site, field, farm, regional, national, and global scales.

Cynthia Rosenzweig

It was also mentioned that the Representative Agricultural Pathways (RAP) are representations of other future aspects of agriculture, not just the changing future climate but also population growth, economic growth, technological development, etc. To fulfill this, we need good data and for this we need to measure it; this can be done on the AgMIP sentinel sites through discussions with the group on how to use this data from experimental sites for modelling purposes, which will be further classified into three categories; Silver, Gold, and Platinum for modelling and finalize the decision rules that apply on them. AgMIP organized to achieve those scientific approaches in four main teams: Climate Team, Crop Modelling Team, Economics Team and Information Technology Team. The work groups were divided into Soil, Water Resources, Livestock and Grasslands, and Pest and Diseases.

All the activities in AgMIP resulted in the following outcomes:

- Improvements and Intercomparisons in Crop Models, Agricultural Economic Models, Scientific Construction, Aggregation Methodologies
- Assessments in regional, global. Crop specific
- Capacity Building and Decision Making in Regular Expertise, Adaptation Strategies, Technology Exchange

Pakistan

The Lead PI of the Pakistan team presented on the topic of Assessing Climate Vulnerability and Projecting Crop Productivity Using Integrated Crop and Economic Modelling Techniques.

The speaker shared that the study was done on rice on a larger scale i.e. for 150 farmers for 5 rice strata and the data collected was given to the crop models in the system. The AgMIP file was prepared with the help of lot of people and then handed over to the economics team. The results for 150 farmers were displayed from an area well known for the production of rice. Each team had nine members from different fields such as economics, crop modelling, meteorological department. A group of five institutes was involved in carrying out the project and the University of Agriculture, as a premier institute, was heading the activity.

A total of five districts were selected for the study on rice, namely Sheikhupura, Sialkot, Nankana Sahib, Gujranwala, and Hafizabad. These are in the northern part of Punjab and more rainfall is found in this area. This area is a very conventional area famous for rice production in Pakistan. For the study of rice, various villages were selected and a climate analysis of the baseline (1980-2010) and future scenario was shown with temperature as a factor. The data collected was of 30 farmers per strata i.e. total of 150 farmers. It was found that the trends for temperature in the future scenario are rising.

Ashfaq Ahmad Chattha

During field survey, management data on the following aspects were collected: previous crops and residues, tillage practices, volume and number of irrigations, seed rates and sowing dates, fertilizer application rates and dates, pesticides application rates and dates, harvesting date and method, harvested and biological yield, and socio-economic variables. Data on initial conditions were collected by district soil laboratories (available water and nitrogen percent). For soil series, data was collected by Federal Soil Survey Department. The Federal Soil Survey Department provided data on pH, organic matter, sand, silt, and clay percentage. Missing values were recalculated by S-Build of DSSAT.

A prerequisite for all the work was that the meteorological data for all locations and the soil series for rice were available. A total of nine soil series were used for study on rice. Three rice cultivars were used in the study of Genetic Coefficient. Subsequently the graphical preliminary results were displayed for fast track farmers field evaluation, relationship between observed

and simulated yield of 150 farmers, frequency distribution of observed rice yield in kilograms per hectare (kg/ha), and frequency distribution of simulated rice yield (kg/ha).

Later on, districtwide (5) results were shown for climate change using RCPs 4.5 and 8.5. The graphs depicted Baseline vs. Near, Mid, and Late Century Scenarios. It was seen that in some cases the gap between the trend lines is more, showing that the climate change is taking place and the farmer will be more vulnerable and we should think and act accordingly to develop adaptation and mitigation strategies. There were also scenarios where the climate change was found to be very minimal due to unique and favourable weather conditions. An overall aggregate graphical depiction for all the 150 farmers was also shown.

AgMIP Pakistan-Datanode components and features were discussed. The AgMIP data node and web portal had been established where all stake holders can put data for sharing purposes, ftp had started working along with posting of data files on secured medium, data merging tools were developed, and two translation software programs were developed for creating new ACMO-files from DSSAT output file.

Yields Summary for Early, Mid and Late Century Scenarios was shown parameters like Base Period Yield (Kgs), Base Period Simulated Yield (Kgs)(S1), Future Simulated Yield (Kgs)(S2), Time Averaged Relative Yield(r), Predicted Future Yield (Time Averaged(Y2) (Kgs), and Crop Model used.

The presentation continued with the preliminary results (without adaptation) of the Aggregated Gains and Losses so far for the Early, Mid, and Late Century Scenarios; the parameters used were Stratum, Climate Scenario, Gainers (%), Gains (As a Percent Of Mean Net Farm Returns), Losses (As a Percent Of Mean Net Farm Returns), and Net Losses (As a Percent Of Mean Net Farm Returns).

Overall adaptation results were also shown. The speaker strongly agreed with the management's idea of coming up with a publication and inviting the stakeholders, as they are the bureaucrats and the policy makers. It was shared that the team was working on a proposed publication for crop modelling and the topics included are as follows: assessing risk, reducing vulnerability, and developing adaptation strategies for food security of rice region, application of DSSAT and APSIM for climate risk management in rice production, and simulating the climate change temporal and spatial variations in the rice region of Pakistan. The topics for the proposed publication for economics are as follows: Vulnerability of Agricultural Systems to Climate Change and Impact of Economic Adaptation on the rice farmers in Punjab, Pakistan; Multidimensional Impact Assessment of the trade-offs caused by climate change: A case of rice farmers of Punjab, Pakistan; Integrated Impact Assessment of adaptation strategies in Punjab: Comparison of different climate and crop models; and Representative Agricultural Pathways: A transdisciplinary approach towards Impact Assessment and adaptation strategies.

Indo – Gangetic Basin

Lead PI of the Indo Gangetic Basin team presented on the topic of Strengthening Simulation Approaches for Understanding, Projecting and Managing Climate Risks in Stress-prone Environments across the Central and Eastern Indo-Gangetic Basin. The study was carried out at

different sites like PDFSR, Meerut, India; CIMMYT, Karnal, India; ICAR-NEH, India; NARC, Nepalganj, Nepal; and BARC, BARI, Bangladesh. A team of knowledgeable members was constructed for the project from these institutes as well as an independent researcher and AgMIP researcher.The Indo-Gangetic basin is divided into three parts: Upper catchments, Western region, and Eastern region. Each region has its own pros and cons in regards to productivity, investment in infrastructure, use of fertilizer, irrigation network, water quality hazards, and migration of laborers.

It was mentioned that climate change impacts are increasingly visible in South Asia with greater variability of the monsoon. It was seen that increases in the occurrence of extreme weather events such as heat waves and intense precipitation affect agricultural production drastically. It was reported that if the current trends continue until 2050, the yields of irrigated crops in South Asia are projected to decrease significantly.The near term goals of the project were to apply crop simulation tools in the major production ecologies of the central and eastern Indo-Gangetic Basin, understand the linkages between climate risks and agricultural productivity, assess the value of adaptation strategies under current and projected climatology while addressing the following question: do current simulation tools and approaches adequately capture the potential of different strategies for building resilience?

Nataraja Subash

The objectives of the project were defined as: segregate the major production domains for cereal crop based production systems and assemble climate, benchmark soil and crop cultivar characteristics for each major production domain for model parameterization and calibration; assess the performance of common crop models (APSIM, DSSAT, INFOCROP) with existing experimental data as well as against district-level data; decompose simulation outcomes to understand the nature and influence of contemporary climate risks in each major production domain; conduct ex-ante evaluations of promising adaptation strategies that respond to major climate risks/projected climate scenarios in each production domain; suggest areas for model improvement that would better represent key processes involved with the development or expression of abiotic stress; and strengthen and broaden the existing simulation modelling network formed through the SAARC initiative.

The site selected for fast track was Meerut, India. In accordance with the handbook, RCP8.5 – Mid Century (2040-2079) was selected as the climate scenario to be used for the study and MIROC5 as the climate model. A comparison of average monthly maximum temperature during baseline (1980-2010) and future (2040-2069) was shown where it was found that the maximum temperature is increasing for the future scenarios and the highest difference was seen in the months of March and April, which are considered a vital time in wheat reproductive stage. A percentage increase/decrease of monthly rainfall during mid-century period 2040-2069 over baseline 1980-2010 was also displayed, showing that monsoon is highest during July and a decrease in rainfall was found in the months after July. For crop modelling in wheat, the crop model selected was the APSIM model. A wide variability in dates of sowing - 17th October to 3rd January was seen. The date of harvest was 10th April - 17th May and five cultivars of wheat were used – PBW223, PBW243, WL502, PBW343, UP232. Variability in N, P, and K applications was also found.

Some assumptions were made, as out of the five dominant varieties of wheat only one of them was considered for the study and it was assumed that potential yields of five varieties were almost the same. Due to lack of data of irrigation depth it was assumed to be five centimeters as recommended irrigation depth. Same was the case for plant density and plant spacing. Soil parameters for seven farms were analysed and were incorporated to the nearby farms. Sentinel data source and treatment details for crop modelling purpose and long term data on nutrient management experiment running for the last 25 years were collected. Other collected data included soil data, crop data (Phenology, LAI, and Biomass partitioning at different phenology, Grain and straw yield), variety and irrigation data. The genetic coefficient used for APSIM wheat calibration was also shown. Calibration of model for crop seasons 2007-08 & 2008-09 was shared through the comparison between simulated and actual yield for both wheat and rice was calibrated and the results found were similar for both simulated and actual. For both biomass and LAI, a time series of observed and simulated yield was shown and it was found that there is minor difference between the observed and simulated yield for biomass but a lot of variation was found in case of LAI.

A comparison of frequency distributions of observed and simulated farm survey wheat yield was shown which was normally distributed. Also a comparison of APSIM simulated wheat yield and observed farm yield was shown which depicted that after some time, the simulated yield is lower than the actual observed yield. A comparison of simulated wheat yield during baseline (1980-2010) and future periods (2040-2069) was shown that in case of baseline period the variability is higher and decrease in yield is greater in comparison to the mid-century period. A percentage decrease of 26.5 was seen in this case. A comparison of distribution of yields simulated for baseline weather and future climate was also shown.

For the interaction with stakeholders a methodology approach was followed, also called the conical approach. It starts at the farm level with an interaction with 140 farmers of the district during farm survey and listing their views and opinions about current climate variability and how they visualize climate change affecting agriculture. At the institute level, multidisciplinary interactive meetings with researchers/ scientists at PDFSR during personal interactions/ group meetings were conducted and some of the problems were solved. At the district level, a stakeholder workshop was conducted and officials of district agricultural development agencies, universities, progressive farmers, researchers of organizations in the district were

invited. Similar activities are proposed at the state as well as the country level as the project included multiple countries.

The RAP narrative was also presented at the workshop, which is comprised of mainly long-term and short-term policy measures, decline of wheat production, labour out migration, farm labour productivity declines, increase in new wheat cultivars, and investment in food chain logistics. Even though the committed site for fast track analysis was just one site i.e. Meerut in India, similar work was done at Bangladesh and Nepal. The results of the analysis were also shown. The gains and losses results were also shared only for one location i.e. Meerut in India. Huge divergence in the group of stakeholders was seen because the farmers are talking more about the non-farming sector issues like increase in farm input cost, transportation facility cost, marketing facility, etc. All the meetings lead to the development of the RAPs.

The main target was to bring all the modellers like crop, economic and climate modellers on a single platform and discuss their needs, work together, and discuss about the issues they are facing during the analysis. A joint boot camp meeting was organized by IGB Project team and SA Regional Coordination Team, ICRISAT during 24-28th June, 2013, at ICRISAT, Hyderabad. The completed tasks included: assemblage of survey data in AgMIP format, simulation of rice/wheat farm yield, historical yield simulation and future yield simulation, development of draft RAPs for different study sites, TOA-MD analysis of different sites, etc. A super DOME was developed by the ARP, to help the rice simulation as after running the model it was not taking the crop establishment as well as the crop file. This issue was solved using the super DOME.

Future plans for integrated assessment were to include more crops to be added for simulation i.e., rice, maize, sugarcane, simulation for predominant cropping system, incorporation of more soil strata and sites because of wide variability in IGB, state level and IGB level stakeholder consultation meeting has to be organized, emerging need is to incorporate livestock and fisheries components in modeling to get more accurate integrated assessment, methodology has to be developed for up scaling the integrated assessment for the entire IGB.

Sri Lanka

The title of this session was Modelling the impacts of a variable and changing climate on rice and sugarcane agricultural systems in Sri Lanka. The project has a large number of collaborators, namely the University of Peradeniya, University of Ruhuna, University of Rajarata, Sugarcane Research Institute, Department of Agriculture and Foundation for Environment, Climate and Technology. The study was carried out in rice and sugarcane dominated systems and field stations. The crop models used to carry out study in the rice dominated areas were DSSAT, APSIM, STICS and AgMIP tools. Similar work was done in the sugarcane producing regions. Climate datasets had been prepared for various locations at Sri Lanka and the progress is being recorded. Temperature and rainfall are the main parameters taken for the study.

In the course of the study farm surveys were conducted at 3 districts, namely Kurunegala district, Matara district, and Ampara district. The details of each farm survey were also presented. A compiled assessment of the results was given which displayed the gains and losses from TOA-MD analysis and gain loss curves for climate scenarios. RAP scenarios were also developed with the team members but more work is needed in their development. Stakeholder

engagement was not comprehensive. There was consultation with National Policy Making and Agricultural, National Agricultural Operational Agencies (Department of Agriculture, Sugarcane Research Institute and Mahaweli Authority), and engagement with farmers and earmer erganizations.

From the IT perspective there was work done for revamping the local crop model for sugarcane developed by Sugarcane Research Institute in 1991, developed using pascal programming language. From the economic perspective, an economic model was developed for integrated sugarcane industry in Sri Lanka.

S P Nissanka

The second speaker from Sri Lanka talked about the status of fast track on rice. It was mentioned that the Kurunegala district was selected to carry out the fast track study as it is the largest district and farmers are involved in irrigated as well as rainfed agriculture. Also the Rice Research Institute is in the same district. The climate data i.e. for Temperature and Rainfall was collected and the future values for the same were predicted.

Along with this a lot of rice variety trials were conducted on different rice varieties for calibration. They collected the experimental data for few varieties and also the data on the coordinated variety trials used for the validation purpose done at two different research institutes. The detailed method of conducting a calibration experiment was explained over two seasons, Yala and Maha. These experiments helped in understanding that the soil can be categorized into three groups and then the farmers were grouped according to the soil groups. These data were entered into the model and farmer yield was calculated. Huge variation was seen and the yield was much lower than observed values. The reason was due to soil variation and necessary reforms were made.

Several meetings and symposia were conducted among the stakeholders. Many short terms as well as medium to long term adaptation measures were proposed. Four adaptation scenarios were identified for future yield simulation: advanced planting date, delayed planting date, replace with the heat tolerant variety, and adjusted planting date with the heat tolerant variety.

Considering these different scenarios, the best option was chosen and it was observed that when the planting date was delayed by one week, the overall yield increased. The increase in yield was also due to the selecting of the variety Bg 300 which is a short term variety and gives better yield under changed climate conditions.

The adaptation results were also shared during the session which shows an increase in yield and decrease in poverty rate with the use of adaptation. A large area of Sri Lanka was covered and in future the same scenarios will be used in other major rice growing seasons. It was also brought to notice that capacity building is given due importance during this project and the major stakeholders for this were the research officers in Department of Agriculture, Research Institutes, Universities, etc.

Southern India

The title of this session was Integrated Assessment of Climate Change Impacts on Principal Crops and Farm Household Incomes In South Asia. The study is being carried out at two locations i.e. Tamil Nadu and Andhra Pradesh. For the whole Tamil Nadu, four different ecosystems were selected from four districts for the study of impact on climate change and water which is one of the limiting resources in the state. Irrigation was classified into four categories: canal irrigation, well irrigation, tank irrigation, and rainfed irrigation. The data used in this study were taken from the ongoing studies, which were further provided to the crop modellers like soil type, variety used, climate system, and irrigation details. For the fast track, climate data were collected for temperature and precipitation for the districts, for both the baselines and the future scenarios. A similar pattern was seen for both the minimum as well as the maximum temperature scenarios. The different models show that there is an increase in the temperature and a decrease in rainfall but the intra year variability remains the same across.

Based on the predictions and crop modelling results, predictions were made for each farmer and it was found that there is a variation across different regions. It was also found that there were no variations found for a single farmer but the variations increased in number when studied across number of farmers. The soil data collected from the different soil profile studies was shared. The soil data was also collected for other study sites from some other sources like the soil science department or the GIS and remote sensing department. The soil found in the study sites is mainly of two categories i.e. clay and sandy loam soil. Nine different rice cultivars and genetic coefficients were used for the study. The data shared with the economic and crop modellers were also shown. The predictions for individual farmers was shown and it was found that there was much less variation for yields of a single farmer, but across multiple farmers, a huge variation can be seen. The cumulative frequency result comparing the crop model projections and the actual survey yields that was gathered from the farmers was also shown.

For Andhra Pradesh, Mahabubnagar District and maize crop were selected. Climate scenario was created for RCP4.5, for the period of 2040-2069, using the GFDL-ESM2G climate model. Similar results were obtained for the minimum and the maximum temperature i.e. an increase was predicted. The other details of the crop model are as follows: Model used: DSSAT- CERES-Maize, Data source: Field experiments conducted at ANGRAU, Hyderabad (2007-2008). A graphical result between the observed and the simulated yield was shown. A comparison of yields simulated for baseline weather and future climate for the same example location and

cumulative frequency distribution with means showing distribution of simulated yields and the observed farm survey yields for the farm survey sites was also shown.

P Parumasivam

Results received from the TOA analysis for both Tamil Nadu and Andhra Pradesh was shared. The analysis units used in the fast track analysis was the per farm analysis and considered only a single stratum and in future, other startas will be taken into consideration for all ecosystems for the study.The future time averaged yields were shared for both Tamil Nadu and Andhra Pradesh. The results were calculated for all GCMs but the results shown were only for one among them as the results were almost similar. When these results were substituted in the TOA model the net loss of 2.84% was found in case of paddy in Tamil Nadu and 3.6% in case of maize in Andhra Pradesh. It was predicted through the results that almost 57% people will be affected by the climate change but the speaker recalled a discussion and remarked about the impact that everybody will be affected, but by keeping in mind the present distribution of perception of farmers of how they are positioned as far as their current yield and their incurring losses these results were presented. Similarly results for Andhra Pradesh were 43%.

Some ideas were given on how to conduct the stakeholder workshops like it should be done before we plan the project and discuss on how to proceed and what are the goals and objectives. Around 25 people were called from the across the state to participate in the RAPs where the views of the participants were taken on some of the variables. A large scale meeting with planners and policy makers was also conducted where results obtained from the earlier stakeholder meeting were shared and the results were acceptable. The speaker shared some interesting experiences and discussions with the farmers and the fellow scientists during the workshops. Similar workshops were conducted by ANGRAU, Andhra Pradesh for maize.

South Asia Regional Coordination Team

The topic discussed by the speaker was Enhancing Capacities of the AgMIP South Asia Regional Teams through Capacity-Building Workshops and Knowledge-Sharing Platforms. The main objectives covered by the project were to build capacity of the multi-disciplinary Research

Teams throughout the region to prepare integrated assessments of climate change impacts and adaptation, to develop learning objects on knowledge-sharing platforms designed to facilitate learning exchanges among and across the various AgMIP regional teams of South Asia, design workshops in collaboration with the AgMIP Leadership Team, and to publish the results of the integrated assessments.

The summary of the work done by the south Asia regional coordination team was shared. This included three workshops, two regional multiple crop training program, IGB boot camp, regional climate training program, and AgMIP South Asia Regional teams' mid-term workshop. The main notion behind was that workshops will build capacity for the AgMIP regional climate assessments and guide projects through assessments to publication.

The workshop is designed in three phases: preparatory phase/ pre-workshop phase, implementation phase and evaluation phase/ post-workshop phase. After defining the goal and objectives of each workshop, the regional research teams will be informed and advised on how to organize their own internal meetings so as to meaningfully prepare for the workshop. In the implementation phase as per the agenda, the workshop activities will be executed to meet the goal and objectives as proposed. In the last phase, Post-workshop activities will be carried out as required such as identifying and planning of regional level training programs (these are small training programs for 15-20 participants).

V V Sumanth Kumar

The main objectives of Multiple Crop Model Training Programs (MCMT) were shared which were to enhance the capacities of the participants, to encourage the facilitation of the use of multiple crop models for simulating crop production variations, to ensure that all the participants got an opportunity to learn a new crop model, so that each RRT team is capable of doing at least two crop models for their project. Many challenges emerged at the MCMTs like greater need of detailed input parameters and related difficulties, issues in collection of soil information of farm, compatibility among software and different crops, difficulty in calibrating the model for all varieties, quality of farm survey data, and accuracy of output.

The salient features of the boot camp and climate training were shared, which were to bring together the climate, crop, and economic modelling scientists of the IGB. All participants completed at least one crop, one crop model, and one site farm survey simulation and completed draft RAPs. There were 12 participants from India, Nepal and Bangladesh. For the climate training, all trainees were able to generate their own climate scenarios using their baseline data. They were able do quality checking and gap filling and develop regional RAPs, which was attended by 24 participants from ANGRAU and private companies. The challenges faced at the boot camp and climate training were shared and were as follows: issues related to the integration of inputs and outputs of different models, issues of APSIM translation tool, inability to use the QuadUI tool for APSIM simulation, no provision of farm survey under AgMIP project, and getting quality of basic information from meteorological stations.

The major outcome of all the activities was to enhance capacities of the AgMIP Research Teams in South Asia and ensure that the teams accomplish the proposed project activities during the project period. A brief of various digital learning resources like KSIConnect, AgMIP Connect (currently not available) were shared. Apart from these resources, some other platforms that can be used for capacity building such as AgEd and can be used for training purposes, delivering of research material, conducting tests, etc., include open access repositories for data, publications, and reports of AgMIP. Virtual interactions to enable knowledge exchanges among and across regional teams, ICRISAT Team, and AgMIP Leadership Team were also discussed.

The proposed focus areas were curriculum development on climate modelling, crop modelling, economic modelling, and specific Requirements of regional Teams, customized training programs for Regional Research Teams, Bbanking on the strength of KSIConnect and AgED Open courseware toward improved capacities of regional participants, Workshop reports & Final Book – South Asia AgMIP Regional Assessment Projects, stakeholder engagement, promoting human resources through train the trainer model on various crop, climate, and economic models to make each team perfect in using all multi models, and need to study the impact different GCMs on their crop yield for their location by RRTs.

Sessions – DAY 5

Pakistan

The title of the presentation was Modelling the Impact of Climate Change on Rice Crop in Rice-Wheat Zone of Pakistan. Pakistan team was working on rice-wheat cropping system. It was shared that rice is planted in the month of June and harvested in the month of October and wheat is planted in the month of November and harvested in the month of April. Five districts from Pakistan were selected for the study, namely Sialkot, Gujranwala, Hafizabad, Nankana Sahib, and Sheikhupura, all known for rice and wheat production. From the climatic perspective it was mentioned that the region selected is closer to the foothills of Himalayas and rainfall is variable across the region but the thermal regime is almost constant.

The RCP8.5 Mid-century temperature and precipitation scenarios were taken for all GCMs and this was done for two areas, Mundiar and Baluki in Pakistan. A significant rise in temperature was seen for both areas. A rise in rainfall was seen in the months of July and August for Mundiar whereas the monsoon peak is shifting from July to August in case of Baluki. Yield prediction data

was collected from five strata for each district. From each district, two villages were selected, the farmers were interviewed, and data were collected. A consistent decrease in yield was found between the baseline and the Mid-century yields of rice.

Muhammad Ashfaq

The Relative Yield Distribution (Mid-Century, RCP 8.5) was discussed for all five strata and a lot of variation was seen. The summary of the economic impact and the distribution of gains and losses were also shared. For the scope of home stretch it was mentioned that the rice and wheat cropping system was used, which are the main crops of the area, the climate scenario taken was mid-century RCP 8.5 using five GCMs. They were also trying the conduct an Impact Assessment using Climate Change Effects along with an Adaptation Impact Assessment. Extensive farm surveys would be conducted for wheat farmers as well as rice farmers.

As part of the adaptation package (Rice-Wheat Zone) the different variables were finalized. For Bio-Physical Factors: change in cropping pattern, improved cultivars, and improved agricultural practices. For Policy Variables – groundwater/surface water policies, subsidy on critical inputs, efficient input/ output markets, government investments in agriculture, implementation of GAP especially for rice, supportive trade policies, and farm consolidation. For Socio-Economic: diversification to avoid risk, optimal use of inputs, participatory management approach, off-farm income opportunities, and agro-forestry. For Others: use of IT tools (climate / market data, etc.), agro-climatic advisory services for farmers, and establish and strengthen interaction among stake-holders.

The deliverables by February 2014 were integrated assessments of rice-wheat system, publications, and establishment of database. Various ideas of extension were also shared including stakeholder engagement and dissemination and outreach.

Indo Gangetic Basin

The title of the discussion was Strengthening Simulation Approaches for Understanding, Projecting and Managing Climate Risks in Stress-prone Environments across the Central and

Eastern Indo-Gangetic Basin. The progress of the work was shared. The study sites were Meerut, Umiam (only rice) and Karnal in India, Nepalganj in Nepal and Dinajpur in Bangladesh. The crop models used were APSIM and DSSAT and simulations were completed for four out of nine simulations to be done.

The rice season is from July to October and wheat season is from November to March. The comparison of the temperature showed an increase in temperature throughout the months. There was a spatial variation of March-May maximum temperature within the district. The spatial variability of weather parameters derived from WorldClim and station data showed a high difference between the higher and the lower values of maximum temperature as well as rainfall which were not correct when seen practically. A comparison of APSIM and DSSAT simulated wheat yield and observed farm yield was shared and it was seen that the DSSAT values were much higher as compared to the observed and the APSIM values above 60% probability but the scenario was reversed below the same probability percentage. A large scale of fluctuation was found in the wheat yield under future scenario when a comparison was done for 34 farmers for baseline and future climate.

Harbir Singh

For the economics analysis, four sites were selected, Meerut (77 farms), Umiam (34 farms), Nepalganj (60 farms), and Dinajpur (30 farms). The analysis was done for both rice and wheat. The comparison could be done using results from APSIM and DSSAT models. When APSIM was used, there was a decline in the yield by 30% and when using DSSAT the yield decline was around 22%. It was also found that Bangladesh would benefit from the climate and no significant change was seen in case of Umiam and Nepalganj.The relative yield distribution showed a difference in case of different models (DSSAT & APSIM). The results in terms of gains and losses were shared. Climate change impact also depicted some difference when the two models were used separately.

The interactions and feedback of the stakeholders was provided in detail for all three countries. For Nepal, MoSTE is the main policy making body, a digital agricultural atlas is being developed, there is a need to prioritize main vulnerable crops and regions, there is lack of information on

mitigation measures, and need for capacity building for climate change and adaptation. For Bangladesh, MoEF deals with issues related to climate change, real time data were not available (floods, draught, cyclones), weak technology delivery system, and no linkages of public extension system with the private sector. For India, no formal action plan for adaptation, NDMA for extreme events, short-term agromet advisory (IMD) by DoAC, District Contingency Plan & mid-term correction, 632 Farm Science Center for information delivery, and expected to double production with available technologies.

Stakeholders' expectations were also shared , such as more sites may be covered under AgMIP plan, CC requires long term strategy, network of institute working on CC in IGB, develop many RAPS for each region, and farming system approach to manage CC and minimize risk. The proposed adaptation package included the adoption of high yielding, short duration, stress (heat/drought/disease and pest) tolerant cultivars, enhancing/altering various management options, and at least three adaptation options would be suggested for each site.

The timeline for the home stretch and the deliverables by February 2014 were discussed during the session. The need and importance of extension was discussed which included the need to develop methodologies for upscaling of district level IA into state/country/ IGB level, crop-livestock-fisheries interaction modelling approach, and organizing of capacity building workshops in the region for crop modelling. The lessons learned from the workshop were discussed, which comprised the need for all the partner institutions to reach same level, so now they can independently work, efforts needed to make the AgMIP tools more flexible, and continue capacity building and hands-on workshops. The future challenges were also discussed in detail.

Sri Lanka

The team from Sri Lanka shared that they were able to clear most of the doubts they had regarding the fast track analysis and also they were able to fine tune the crop modelling, climate modelling, and TOA-MD shortcomings they had earlier. Based on the advice given, the work improved and work still needs to be carried out. The updates of the crop, climate, TOA-MD modelling and how the home stretch was going to be carried out were presented. Experts from different sections presented the major updates that took place during the workshop. The first speaker talked about the climate of the home stretch region. The region selected for climate study was Batalagoda representing the Kurunegala rice growing area. Intentions to increase the number of study stations was shared. Based on the present study some interesting things came forward. Variation of temperature and rainfall during the year was seen in the lower part of the diagram. Four models were used; the first one showed that it had captured the temperature change over the month; the second graph showed the rainfall variation between the baseline and the mid-century is very marginal but there was a slight increase in the second half of the Maha season and also in October there was a drop in rainfall. No significant difference was seen in the Yala season between the baseline and the mid-century rainfall. The model also captured the rainfall distribution of the region. A consistent increase in temperature was found in the region for both the seasons.

Lareef Zubair

The next speaker explained about what has happened regarding the improvement done in calibration for the rice varieties based on the suggestions given for one cultivar (BG 357). The team got three detailed experiments and tested for 22 coordinated rice variety trial experiments, from which we got only phenology and yield. The information of the experiments was used to derive the genetic coefficients. The results received were an improvement from the previous results and the same approach will be used for other cultivars as well.

The next speaker shared the updated TOA-MD results. The parameters taken for the study were corrected period – normalized yield, predicted yield, relative yield, and net loss. The results depicted that almost 30% of the farmers will be benefitted by the climate and the net losses will be around 15%.

The stakeholder views and the scope for home stretch were discussed in detail. The adaptation package for rice was mentioned and it consists of adjusting planting window, introduction of better adapted varieties, use of potential rice varieties to adapt heat tolerance better, development of genetic coefficients for more tolerant varieties, diversification of minor season crops, and application of traditional information. The timeline was discussed and then the reasons for the extension of the project were discussed. The reasons given were as follows: An extension shall enable the team to really consolidate and be more definitive in outcomes; the areas covered (for both rice and sugarcane) limit the generalization of output, as there is considerable agro-ecological and socio-economic diversity across Sri Lanka; work going on in parallel (especially sugarcane) can be brought to a completion (fruition); ensuring development of capacity sustainably; and proper engagement with policy makers requires in-depth work and robust results.

Southern India

The report by South Asia presented the overview of the baseline agroclimatic analysis which was covered under the fast track and will be covered in the extended analysis. The results started with the depiction of the growing season for rice i.e. September/October to December/

January, which is the northeast rainy season for Aduthurai, Tamil Nadu. A comparative analysis of the baseline yield was conducted with the baseline rainfall, baseline minimum temperature, and the baseline number of rainy days. A positive relationship was seen between the yield and the amount of rainfall and the number of rainy days. On the other hand, a negative relationship was found between the yield and the minimum temperature. Similar results were obtained for the Maize crop in Mahabubnagar, Andhra Pradesh. But a shift was seen in the results during the time period of 1995 and the reason was predicted as the increase in the stress days during the reproductive stage.

A study on the Spread of Temperature and Rainfall Changes in 20 CMIP5 GCM Simulations of Mid-Century RCP 8.5 was done for both the rainy seasons for Tamil Nadu and similarly for south west monsoon of Mahabubnagar, Andhra Pradesh. In case of Andhra Pradesh we found a shift in temperature towards the positive side that means all the models are projecting increase in temperature and an increase in rainfall is also shown by most of the models. The variability was found to be much lesser in Andhra Pradesh than in Tamil Nadu. The north east monsoon is the major rainy season of Tamil Nadu and a positive shift is seen in case of temperature while in case of rainfall is found to be lower in growing season. Also, it was mentioned that the southwest monsoon is more stable than the northeast monsoon.

Vellingiri Geethalakshmi

A comparison was done for the baseline with the future climate with RCP8.5 Mid-Century temperature scenarios for both seasonal and annual. It was found that for Mahabubnagar, the temperature for the growing season was elevated and a variation in rainfall was identified for the growing season. Among the growing season the month of June was expected to get higher rainfall, but the months of July, August, and September would receive either similar or less rainfall. A higher temperature was expected in Tamil Nadu in all the seasons and in case of rainfall it was expected to increase in the month of November. In case of rainfall, it was expected to be less than the baseline in the months of June, July, August, and September. At the same time, the temperature was increasing in all the cases even in the growing season. Higher rainfall was

expected during October, November, and December, as it is the main growing season at the same time temperature was also expected to increase.

A graphical representation of the relative yield distribution was also shared. The results for Andhra Pradesh were much more spread out in comparison to Tamil Nadu. The gains and losses were also shared for both the states. The summary of the economic analysis was discussed. Later the scope of home stretch was discussed and the crops and the sites are mentioned which were used for the study in future also. Holistic view of the approach to address climate change / variability was also discussed in detail. The cropping system along with livestock was addressed in the approach and used to calculate the net gain and loss. Similar approach is planned in Andhra Pradesh also.

The adaptation package was discussed which comprised of the crop models and the economic models. There were four crop models, namely water management, varietal change, N management, and dates of planting. Among these, water management was given more importance due to the water-constrained nature of the area. The delivery timeline for the study and some ideas for extension were also shared.

South Asia Regional Coordination Team

The speaker provided a summary of the work done by all the teams and the results of the workshop. The results were divided in three parts: crop modelling, climate modelling, and economic modelling. The status report of the crop modelling was presented and the work was divided into three categories: Completed, In progress and Future Course of Action. Under crop modelling for IGB India, APSIM Rice and APSIM Wheat are completed, DSSAT Wheat was in progress, and DSSAT Rice was under Future Course of Action. For IGB Nepal, APSIM Wheat was completed, DSSAT Rice and APSIM Rice was in progress, and DSSAT Wheat was under Future Course of Action. For IGB Bangladesh, APSIM Rice was completed, APSIM Wheat was in progress, and DSSAT Rice and DSSAT Wheat were under Future Course of Action.

For Sri Lanka, DSSAT Rice was in completed stage but more work was required and APSIM Rice, APSIM Sugarcane, and DSSAT Sugarcane were under Future Course of Action. For Pakistan, DSSAT Rice and DSSAT Wheat were completed, APSIM Rice and APSIM Wheat were in progress, and APSIM Cotton was under Future Course of Action but yet to decide whether to do or not. For South India, DSSAT Maize and DSSAT Rice were completed, APSIM Rice was in progress, and APSIM Maize was under Future Course of Action. Under economic modelling, the Fast Track was done by all the teams and for IGB Bangladesh and Sri Lanka minor fine tuning in the results is required. For Home Stretch, the case studies were presented by all the teams. Under climate modelling all the teams were found to be empowered with the techniques of how to do the climate modelling.

The various issues expressed by the regional research teams regarding the IT tools were also discussed in detail for the different models like DSSAT Rice and APSIM Rice. Some immediate needs of the regional research teams were also discussed in terms of the capacity building needs for the teams. IGB for DSSAT -Rice, Wheat, South India -APSIM-Rice, Maize for Andhra Pradesh & Tamil Nadu, Sri Lanka- APSIM-Rice, STIC-Rice and DSSAT-Sugarcane , APSIM-Sugarcane and Pakistan - APSIM Rice, Wheat, Cotton.

G Dileepkumar

The coordination team also presented an action plan which consisted of conducting AgMIP Home Stretch Sprints which will be facilitated by CRT experts backed up by experts from Leadership team to be held at Sri Lanka (September 2013). There was a need for participants to be experienced model users and they should have model ready datasets. Also there was a need expressed to identify leadership team experts/E-experts. Periodical research discussions using web technologies as face-to-face meetings are expensive and sometimes it's not possible to bring all the people together. So, it was proposed that bi-weekly virtual meeting on specific issue/monthly update/need based to be conducted. It was considered ideal to plan the Advance Intensive Workshop on Integration and Interpretation in December 2013, as teams can be ready with their results and can come interpret them with the help of the leadership team and after this they can further use the interpreted results for the final reports.

As part of the action plan of the CRT, preparing RRTs for Upcoming Events in terms of providing the templates for the posters and the assistance in building up the chapters and the follow-up mechanism was discussed. Also preparation for the AgMIP Global Annual Meeting, ASA was shared. For effective contribution to the scale up operation that was planned for future, some other points regarding the action plan were shared, which included the creation of regional expert trainers to document methodologies, issues, best practices to enhance learning materials, for creation of learning objects, to develop knowledge products, outreach and dissemination through knowledge products and platforms, and engagement and coordination of stakeholders.

The time line for the activities was shared along with the ideas for extension which included stakeholder engagement and synergies to work with national projects, dissemination and outreach through knowledge products and platforms, improve human resources through capacity building activities and student scholarship program, and design and development of AgMIP knowledge base.

Breakout Sessions

The Fast Track results from each regional team were reviewed and economic components were corrected as required for the team. The economic team discussed the revised methods for incorporation of time variation in yields from crop simulation model. The protocol of linking crop simulation results with economic models was also discussed and made clear to the regional team to implement in the fast track analysis and the results were revised and presented in the plenary session of the workshop. The methods for incorporating additional crops which is not part of the crop modeling exercise were discussed. And also the incorporation of livestock component was also discussed. The issues in fast track exercises were addressed in some of the regional projects in advanced stages. Extension of the model to whole farm systems and complete climate impact and at least one adaptation scenario were modeled. Also, the revised protocol from implementing the crop model simulation results were presented to the regional economic team and explained for implementing in the whole farm modeling exercise. The RAPS construction and various issues in developing the adaptation strategies were discussed with the team. The regional teams presented their concern in developing RAPS.

The interpretation of the economic modeling results were discussed and made clear on how to present the TOA-MD results and graphs to explain the results. The price and yield projections for the region or country for developing the RAPS narrative were discussed and global economic modeling projection results required for the regional teams from different SA countries will be provided by Global Regional economic team.
Discussions were held for conducting Sri Lanka Boot camp, to polish, analyze, understand, justify, interpret and present the modelled data, keeping the following principles in mind:

1. Not training, but doing the 'home stretch' analyses, supported by experts, 2. Need is greatest in Sri Lanka. Also include some participants, who are at a similar skill level, from other areas with need (e.g. Pakistan), 3. Participants need to be experienced model users, 4. Participants need to have already modelled the data, 5. CRT staff can contribute to the role of experts and need to define their vision for the long-term, role of CRT team members as regional resource people and experts, and how to use the boot camp to facilitate the transition into this role.

The tasks to be taken to fulfill the principles discussed were:

1. Need to prepare a Participant list, 2. Preparatory work needed by participants and CRT members, 3. To bridge the expertise need, identifying external experts in crop modelling and economics needed, 4. Identify e-experts needed to provide additional support, 5. Date and venue needs to be decided (subject to travel constraints of participants) along with logistical details (e.g. letter invitation to those who need it).

The AgMIP Leadership team interacted with IGB Project team on 23rd July, 2013, to take stock of the work progress and future plans in view of the project objectives and goals. During the interactions, the IGB team briefed about the challenges being faced with cropping system simulation, as the validated model capturing farming system as a whole is not available. The AgMIP leaders also asked the team to prepare a system diagram for a better understanding of the existing farming systems in their respective study region. After meeting the AgMIP Leaders, the IGB team held interactions with the stakeholders as per the programme. During the interactive session with the stakeholders, the importance of farming system approach was

emphasized to sustain the agricultural productivity under projected climate change scenarios as well as under the extreme weather variability situations. The stakeholders also briefed the team about the decision making process in their respective countries to deal with the climate change impacts and adaptation strategy. In the afternoon, methodological challenges and multi-disciplinary issues were discussed in the team breakouts. In the plenary session, each project team presented the progress and outcome of the day report.

On the 24th July, all the RRTs kept working on result updates and refinements in the morning. The resource persons also clarified certain methodological issues and project protocols. In the afternoon session, the organizer arranged a field trip to Bhaktapur district of Nepal to show the existing farming system in the countryside to all the workshop participants. The following day (25th July), a presentation was made on the research goals for the remainder of the project to sensitize all the teams about the remaining work to be completed. The speaker also presented a Coordinated Climate Crop Modeling Project (C3MP) and invited interested modelers to join in the proposed project. Thereafter, all the RRTs kept working on finalizing the results from fast track. Several issues related with AgMIP tools for running APSIM rice and wheat were discussed and informed the issues to the leadership. The last day (26th July) goal was to finalize workshop reports and future work plan. The RRTs finalized their workshop report. Thereafter, all the regional teams presented workshop report and future plans in the plenary session.

Conclusion

The regional research teams assessed the fast-track evaluations and planned the completion of their regional assessments by meeting with AgMIP PIs and crop, climate, economic, and IT leaders. The teams also met independently to further their integrated assessments on the impact of climate change on agriculture in their region. The workshop enabled the continuation of joint advancement of integrated assessments of the impact of climate change on agriculture in specific regions of South Asia. It also provided opportunities for interactions between researchers and stakeholders

Attendees of AgMIP South Asia Mid-Term Workshop Kathamndu, Nepal.

Annexure 1: Agenda

Regional Research and Coordination Team

Mid-Term Workshop

South Asia Teams

Hotel Annapurna, Durbar Marg

Kathmandu, Nepal

July 22-26, 2013

Final Program

Overall workshop goals:
1) Demonstrate the accurate completion of the mid-term workshop checklist
2) Work together on multidisciplinary analysis of simulation results
3) Ensure that each team has clear work plan to achieve full project goals
4) Work on post-fast-track integrated assessments, analyses, and publications
5) Develop plan for dissemination of AgMIP results to inform stakeholder actions

Day 1 - Monday, 22 July
Goals: 1) Provide overview on "state of AgMIP" to the teams and stakeholders
2) Assess overall progress of teams and disciplinary leaders to date
3) Conduct facilitated discussion with Stakeholders

08:00 **Registration**

08:30 Welcome and Introductions, Workshop goals – J Jones

09:00 Official opening speech – C Rosenzweig

09:20 State of AgMIP – C Rosenzweig

10:00 Regional Research Team (RRT) presentations based upon Mid-term Workshop Report-in Template

Indo-Gangetic Basin

Pakistan

10:40 **Tea/Coffee Break**

11:10 Continue Regional Project Presentations

Sri Lanka
South India
Regional Coordination Team (CRT)

12:10 Discussion

12:30 **Workshop Photo, Lunch**

14:00 Charge to afternoon breakouts – P Craufurd

14:15 Climate, Crops, Economic, and Coordination Team breakouts

- RRT members breakout by expertise
- Present Mid-term checklist results in detail
- Determine methodological challenges for workshop
- CRT meets with stakeholders

15:30 **Working Tea/Coffee Refreshment**

17:00 Facilitated discussion with stakeholder inputs – C Rosenzweig

18:00 **Adjourn for the day**

18:30 **Reception**

Day 2 – Tuesday, 23 July

Goals: 1) RRT interactions with stakeholders
2) CRT facilitates stakeholder interactions and learning among groups
3) Leaders review and evaluate progress of each team

08:30 Plenary Session - Review workshop goals, day's goals – J Jones

08:45 Charge to RRT/CRT breakout groups – P Craufurd

09:00 RRTs meet with stakeholders from region to discuss progress, aims, and potential outcomes. Each team will also have a 45 minute technical session to meet with the AgMIP leaders for feedback and guidance on next steps (this technical session will not include stakeholders). CRT members disburse among RRTs to learn more about each regional project and its stakeholder objectives.

09:00 Indo-Gangetic Basin visits Leaders
09:45 Pakistan visits Leaders

10:30	**Working Coffee/Tea Refreshment**
10:45	Sri Lanka visits Leaders
11:30	South India visits Leaders
12:15	CRT visits Leaders
13:00	**Lunch**
14:00	Plenary Session – Charge to RRT Breakouts – P Craufurd
14:15	RRTBreakouts – methodological challenges and multidisciplinary assessment
15:30	**Working Coffee/Tea Refreshment**
17:30	Plenary - Report Back - Review next day plans – C Rosenzweig& J Jones
18:00	**Adjourn for the day**

Day 3 – Wednesday, 24 July
Goals: Continue RRT & CRT work

08:30	Plenary Session – Goals for Day 3 – C Rosenzweig
08:45	Charge to RRT Breakouts – P Craufurd
09:00	RRT Breakouts
10:30	**Working Coffee/Tea Refreshment**
13:00	**Lunch**
14:00	**Field Trip – Chittapole VDC of Bhaktapur District**
18:30	**Return**

Day 4 – Thursday, 25 July
Goals: Continue RRT and CRT work, design work priorities for remainder of project

08:30	Plenary Session – Results from Day 3, goals for Day 4 – J Jones
08:45	Charge to Team Breakouts – P Craufurd
09:00	Team Breakouts – Leaders Breakout & Float as needed

10:30	**Working Coffee/Tea Refreshment**
13:00	**Lunch**
14:30	Plenary – Research goals for remainder of Project – A Ruane
15:05	Plenary – Data Plan – J Jones
15:15	**Working Coffee/Tea Refreshment**
15:30	RRT Breakouts– Organize workshop reports and assess priorities for the remainder of the project
17:00	Plenary - Report Back - Review next day plans – C Rosenzweig& J Jones
17:30	The Coordinated Climate Crop Modeling Project (Optional) – A Ruane
18:30	**Adjourn for the day**

Day 5 Friday, 26 July

Goals:	Teams and Leadership finalize work plans and workshop reports
08:30	Plenary -Goals for Day 5 – C Rosenzweig& J Jones
08:45	RRT Breakouts & Leaders Breakout – Finalize workshop presentations and create work plan for remainder of project including potential publications
10:15	**Working Coffee/Tea Refreshment**
10:45	**Plenary** – RRT & CRT Reports – 45 minutes each – status and plans
10:45	Indo-Gangetic Basin
11:30	Pakistan
12:15	Sri Lanka
13:00	**Lunch**
14:00	**Continue Plenary**
14:00	South India
14:45	Coordination Team
15:30	**Feedback from leadership, Discussion**
17:00	**Adjourn**

Annexure 2: Participants

South Asia Regional Research and Coordination Team Mid-Term Workshop

22-26 July 2013

Hotel Annapurna, Kathmandu, Nepal

List of Participants with full contact information

Name	Address	Contact information
AgMIP Leaders – 14 Persons		
Dr Cynthia Rosenzweig	AgMIP PI, NASA Goddard Institute for Space Studies, 2880 Broadway, New York, NY 10025, USA	E: crr2@columbia.edu; crosenzweig@giss.nasa.gov
Dr Jim Jones	AgMIP PI, Florida Climate Institute, 289 Frazier Rogers Hall, PO Box 110570, Gainesville, FL 32611, USA	E: jimj@ufl.edu
Dr Kenneth Boote	AgMIP Crop Modeling PI, 304 Newell Hall, PO Box 110500, Gainesville, FL 32611, USA	E: kjboote@ufl.edu
Dr GerritHoogenboom	AgMIP Resource Person; Director, AgWeatherNet, and Professor of Agrometeorology, Washington State University, 24106 North Bunn Road Prosser, Washington 99350-8694, USA	E: gerrit.hoogenboom@wsu.edu
Dr Carolyn Z Mutter	AgMIP International Project	E: czm2001@columbia.edu

	Coordinator, Columbia University, Center for Climate Systems Research, Armstrong Hall - 2880 Broadway, New York, NY 10025, **USA**	
Dr Roberto Valdivia	Economics, Ballard Extension Hall, Oregon State University, Corvallis, OR 97331, **USA**	E: roberto.valdivia@oregonstate.edu
Dr Peter Thorburn	Senior Principal Research Scientist, Leader: Northern Farming Systems Research Group, CSIRO Ecosystem Sciences, CSIRO Ecosystem Sciences, GPO Box 2583, Brisbane QLD 4001, **Australia**	E: peter.thorburn@csiro.au
Dr John Antle	AgMIP Economics PI, Rm #220A Ballard Extension Hall Oregon State University, Corvallis, OR 97331, **USA**	E: John.Antle@oregonstate.edu
Dr Daniel Wallach	AgMIP Resource Person, INRA, UMR1248, BP 52627 F-31326 Castanet-TolosanCedex, **France**	E: wallach@toulouse.inra.fr
Dr Alexander Ruane	AgMIP Climate PI, Research Physical Scientist, Climate Impacts Group, NASA GISS, 2880 Broadway, New York NY 10025, **USA**	E: aruane@giss.nasa.gov
Dr Guillermo A Baigorria	AgMIP Resource Person, 261 Frazier Rogers Hall, Agricultural and Biological Engineering Dept., Gainesville, FL 32611, **USA**	E: gbaigorr@ifas.ufl.edu (Old); gbaigorria@unl.edu
Dr SonaliMcDermid	AgMIP Resource Person, NASA Goddard Institute for Space Studies, 2880 Broadway, New York, NY 10025, **USA**	E: sps2113@columbia.edu Sonali.p.shukla@nasa.gov
Ms Shari Lifson	Communications Coordinator, Columbia University, Center for Climate Systems Research, Armstrong Hall - 2880 Broadway, New York,	E: sll2158@columbia.edu

	NY 10025, USA	
Dr Govinda Joshi	GIS Analyst, International Centre for Integrated Mountain Development, GPO Box 3226, Kathmandu, **Nepal**	E: gjoshi@icimod.org
Pakistan – 13 Persons		
Dr Ashfaq Ahmad Chattha	Director External Linkages Incharge Climate Change Cell, University of Agriculture, Faisalabad, **Pakistan**	E: aachattha1@yahoo.com; del@uaf.edu.pk; agmip@uaf.edu.pk
Dr GhulamRasul	Chief Meteorologist, Pakistan Meteorological Department, PitrasBukhari Road, H-8-2, Islamabad, **Pakistan**	E: grmet@yahoo.com; rasulpmd@gmail.com
Dr Muhammad Ashfaq	Professor and Director, Institute of Agricultural and Resource Economics, University of Agriculture, Faisalabad 38040, **Pakistan**	E: ashfaq9@hotmail.com; mashfaq@uaf.edu.pk
Dr Syed AftabWajid	Co-PI, Associate Professor Dept of Agronomy, University of Agriculture, Faisalabad, **Pakistan**	E: aftabwajid@hotmail.com
Dr WajidNasim	Co-PI, Asst. Professor, Dept. of Environmental Science, COMSATS-Institute of Information Technology (CIIT), Off Multan Road, Vehari 61100, **Pakistan**	E: wajidnasim@ciitvehari.edu.pk; Wajidnaseem2001@gmail.com
Dr Shakeel Ahmad	Co-PI, Crop modelling, Associate Professor (Agronomy), BahauddinZakariya University, Multan-60800, **Pakistan**	E: shakeelahmad@bzu.edu.pk
Mr KashifRazzaq	Data Entry Operator (IT), AgMIP-Pakistan, Department of Agronomy, University of Agriculture, Faisalabad, **Pakistan**	E: mkashifrazzaq@gmail.com

Dr JamshadHussain	Research Officer, Agro-Climatology Lab., Department of Agronomy, University of Agriculture, Faisalabad, **Pakistan**	E: mjamshad18@gmail.com
Mr Syed Asif Ali Naqvi	Research Officer (Economic Group), Institute of Agricultural and Resource Economics, University of Agriculture, Faisalabad 38040, **Pakistan**	E: syedasif_1@yahoo.com
Mr Syed Ahsan Ali Bokhari	Electronic Engineer, Climate Group Pakistan Meteorological Department, PitrasBukhari Road, H-8/2, Islamabad, **Pakistan**	E: ahsan.pmd@gmail.com; ahsan@pmd.gov.pk
Dr TasneemKhaliq	Co-PI (Crop Modelling Group)/ Assistant Professor, Department of Agronomy, University of Agriculture, Faisalabad, **Pakistan**	E: tasneem1056@hotmail.com; drtasneem@uaf.edu.pk
Dr Irfan Ahmad Baig	Assistant Professor, Department Economics, PMAS Arid Agriculture, University, Rawalpindi, **Pakistan**	E: irfybaig@gmail.com
Dr Fahd Rasul	Assistant Professor, Department of Agronomy, University of Agriculture, Faisalabad, **Pakistan**	E: drfahdrasul@gmail.com; drfahdrasul@uaf.edu.pk
South India - 7 persons		
Dr P Paramasivam	Professor, Department of Agricultural Economics, Tamil Nadu Agricultural University, Coimbatore-641 003. Tamil Nadu, **India**	E: params@tnau.ac.in
Dr A Lakshmanan	Professor, Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore-641 003. Tamil Nadu, **India**	E: lakshmanantnau@yahoo.com; microlaxman@yahoo.com
Dr Vellingiri Geethalakshmi	Professor, Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore -641 003, Tamil Nadu, **India**	E: geetha@tnau.ac.in

Dr R Balasubramanian	Professor, Department of Agricultural Economics, Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, **India**	E: rubalu@gmail.com
Dr D Suresh Kumar	Professor, Department of Agricultural Economics, Tamil Nadu Agricultural University, Coimbatore-641 003. Tamil Nadu, **India**	E: rithusuresh@yahoo.com
Dr Raji Reddy Danda	Director, Agro Climate Research Centre, ARI, ANGR Agricultural University, Rajendranagar, Hyderabad, AP, **India**	E: dandareddy009@gmail.com
Dr MedhaDakshina Murthy Kadiyala	Scientist – Agronomy, Agro Climate Research Centre, ARI, ANGR Agricultural University, Rajendranagar, Hyderabad, AP, **India**	E: dakshu2k@gmail.com
Indo-Gangetic Plains – 13 persons		
Dr BGangwar	Project Director & Team Leader-AgMIP-IGB Project, Project Directorate for Farming Systems Research, Modipuram-250110, Meerut, Uttar Pradesh, **India**	E: directorpdfsr@yahoo.com
Dr NSubash	Lead PI of AgMIP-ICAR Project, Senior Scientist, Project Directorate for Farming Systems Research, Modipuram-250110, Meerut, Uttar Pradesh, **India**	E: n_suby@rediffmail.com
Dr Harbir Singh	Co-PI of AgMIP-ICAR Project, Principal Scientist, Project Directorate for Farming Systems Research, Modipuram-250110, Meerut, Uttar Pradesh, **India**	E: hs.pdfsr@yahoo.com
DrAnup Das	Senior Scientist (Agronomy), ICAR Research Complex for NEH region, Umiam, Meghalaya-793103, **India**	E: anup_icar@yahoo.com

Dr B U Choudhury	Senior Scientist, Division of Soil Science, Indian Council of Agricultural Research Complex for NEH Region, Umiam, Meghalaya-793 103, **India**	E: burhan3i@yahoo.com
Dr K P Mohapatra	Senior Scientist, ICAR Research Comlex for NEH Region,Umiam - 793103, Meghalaya, **India**	E: kpmbbsr@gmail.com
Dr Gokul Prasad Paudel	Socio-economist, Socio-economics Program, International Maize and Wheat Improvement Center, CIMMYT South Asian Regional Office, Kathmandu, **Nepal**	E: g.paudel@cgiar.org
Dr Krishna Devkota	Post Doctoral Cropping Systems Scientists, CIMMYT South Asian Regional Ofiice, Kathmandu, **Nepal**	E: k.devkota@cgiar.org
DrRajendraDarai	Senior Scientist, National Grain Legumes Research Program, Nepal Agricultural Research Council, Rampur, Chitwan, **Nepal**	E: rajendra5042@yahoo.co.uk
Dr Dinesh BabuThapaMagar	Socio-Economist, Socio-Economics and Agricultural Research Policy Division (SARPOD), Nepal Agricultural Research Council (NARC), Kathmandu, **Nepal**	E: darlami.dinesh@gmail.com
Dr SohelaAkhter	Principal Scientific Officer, Soil Science Division, Bangladesh Agricultural Research Institute (BARI), Gazipur-1701, **Bangladesh**	E: sohela_akhter@yahoo.com; sohela@bangla.net
Dr MdKamrulHasan	Principal Scientific Officer, Planning and Evaluation Division, Bangladesh Agricultural Research Institute (BARI), Gazipur-1701, **Bangladesh**	E: khasan41@yahoo.com
Mr Apurbo Kumar Chaki	Scientific Officer (Agronomy), On -Farm Research Division (OFRD), Bangladesh Agricultural Research Institute (BARI), Gazipur-1701,	E: apurbochaki@yahoo.com

	Bangladesh	
DrSkGhulamHussain	Independent Researcher, Former Member-Director (Planning & Evaluation) Bangladesh Agricultural Research Council, **Bangladesh**	E: ghussain@agni.com; hussain@hussainsg.net
ICRISAT – 9 persons		
Dr Peter Q Craufurd	Research Program Director, Resilient Dryland Systems, **ICRISAT, Patancheru PO 502324, Andhra Pradesh, India**	E: p.craufurd@cgiar.org
Dr G Dileepkumar	Global Leader, Knowledge Sharing and Innovation and Coordinator for ICRISAT South-South Initiative, ICRISAT, **Patancheru PO 502324, Andhra Pradesh, India**	E: g.dileepkumar@cgiar.org
Dr V V Sumanth Kumar	Scientist-ICT4D, Knowledge Sharing and Innovation, ICRISAT, Patancheru PO 502324, Andhra Prdesh, **India**	E: v.sumanth@cgiar.org
Mr Chukka SrinivasaRao	Senior Manager-DMU, Knowledge Sharing and Innovation, ICRISAT, Patancheru PO 502324, Andhra Prdesh, **India**	E: s.chukka@cgiar.org
Dr NedumaranSwamikannu	Scientist-Economics, **Markets, Institutions and Policies, ICRISAT, Patancheru PO 502324, Andhra Pradesh, India**	E: s.nedumaran@cgiar.org
Dr Piara Singh	Consultant, **Markets, Institutions and Policies, ICRISAT, Patancheru PO 502324, Andhra Pradesh, India**	E: p.singh@cgiar.org
Mr S V Prasad Rao	Senior Administrative Officer, Knowledge Sharing and Innovation, ICRISAT, **Patancheru PO 502324, Andhra Pradesh, India**	E: s.prasadrao@cgiar.org

Mr D VenkateshwaraRao	Technical Officer, Knowledge Sharing and Innovation, ICRISAT, **Patancheru PO 502324, Andhra Pradesh, India**	E: d.v.rao@cgiar.org
Sri Lanka - 12 Persons		
Dr Lareef Zubair	Co-PI, Foundation for Environment, Climate and Technology (FECT), Digana Village, Rajawella, **Sri Lanka**	E: lareefzubair@gmail.com
Dr S P Nissanka	PI, Department of Crop Science, University of Paradeniya, **Sri Lanka**	E: nissankasp@yahoo.com; spn@pdn.ac.lk
Dr A P Keerthipala	Director and Economics, Sugarcane Research Institute, Udawalawe, **Sri Lanka**	E: apkeerthipala@yahoo.com
Dr W M W Weerakoon	Co-PI, FCRDI, , Department of Agriculture, Field Crops Research and Development Institute, Mahaillupallama, **Sri Lanka**	E: weerakoonwmw@gmail.com
Prof K D N Weerasinghe	Department of Agricultural Engineering, University of Ruhuna, **Sri Lanka**	E: kdnweerasinghe@outlook.com; kdnw@ageng.ruh.ac.lk
Mr DumindaIndikaHerath	Econ/Climate, Foundation for Environment, Climate and Technology, C/o Mahaweli Authority, Digana Village, Rajawella, **Sri Lanka**	E: duminduherath@gmail.com
Prof Piyasena Wickramagamage	Head, Department of Geography, University of Peradeniya, **Sri Lanka**	E: wickramagge@yahoo.com
Dr R M Herath	Economist, Department of Agriculture, University of Peradeniya, Peradeniya, **Sri Lanka**	E: herath.rasnayaka1@gmail.com
Dr AshaSajeewani Karunaratne	Senior Lecturer, Faculty of Agricultural Sciences, Sabaragamuwa University, Belihuloya, **Sri Lanka**	E: asha.karunaratne@yahoo.co.uk; asha.karunaratne@cffresearch.or

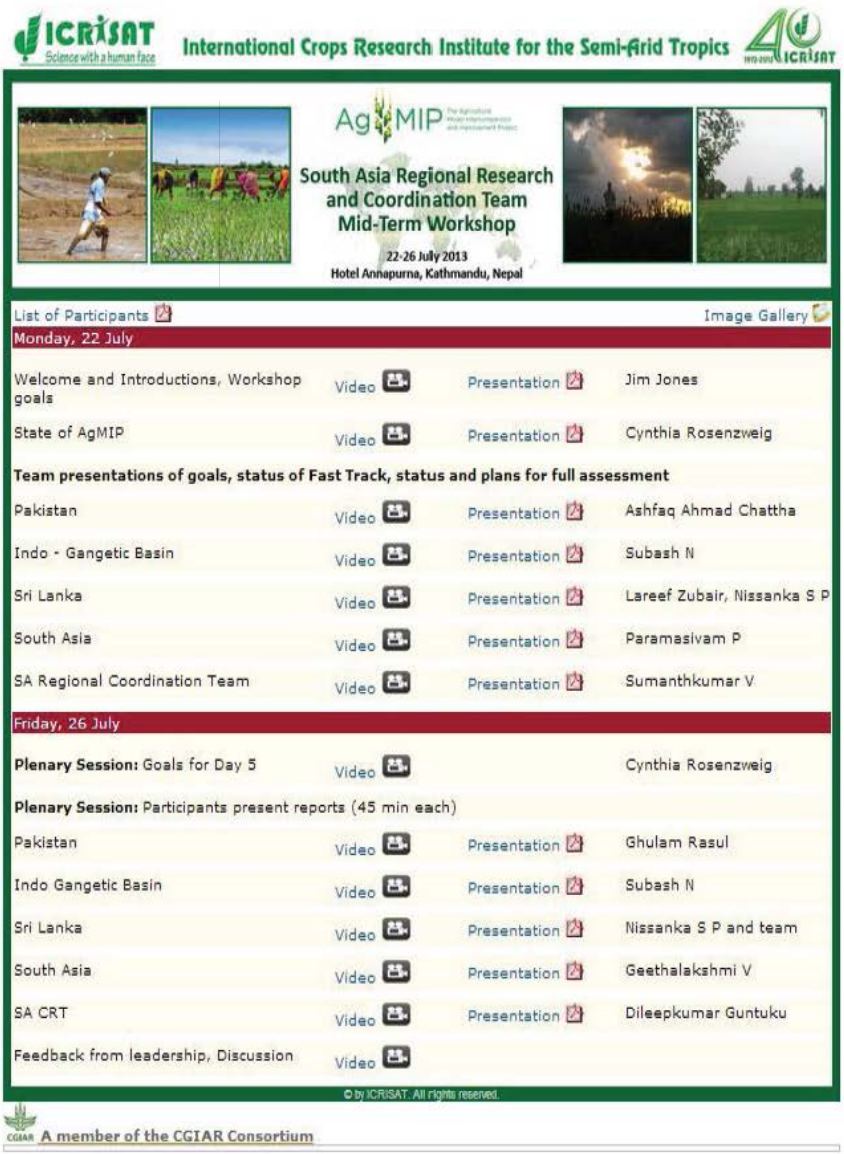
		g
Ms ErandikaNiroshini Wijekoon	Research Economist, Foundation for Environment, Climate and Technology, Digana Village, Rajawella 02, **Sri Lanka**	E: erandikawijekoon@gmail.com
Mr RatnayakeMudiyanselegedaraSanjayaPrabodhaRatnayake	Research Scientist, Foundation for Environment, Climate and Technology, Digana Village, Rajawella, **Sri Lanka**	E: sanjurat@yahoo.com
Mr A S M PrabodhaMalinga BandaraAgalawatte	Foundation for Environment, Climate and Technology, Digana Village, Rajawella, **Sri Lanka**	E: pr.agalawatte@gmail.com

List of Stake Holders

Name	**Address**	**Contact information**
Dr Arvind Kumar	Deputy Director General (Education), KAB- II, Indian Council of Agricultural Research, New Delhi- 110012, **India**	E: ddgedn@icar.org.in; ddgedn@gmail.com
Mr Manzoor Ahmad Khan	27 -T, DHA , Lahore, **Pakistan**	E: manzoorkhan@hotmail.com
Mr S K Cyril	Chairman, Sugarcane Research Institute, Phelawala Road Ratmalana, **Sri Lanka**	E: cyrilsk@hotmail.com
Mr Piyush Dhal	Program Coordinator, The Small Earth Nepal,626 Bhakti ThapaSadak, NayaBaneshwor, P O Box 20533, Kathmandu, **Nepal**	E: piyush@smallearth.org.np

Dr YubakDhoj G.C	Director General (Entomologist-IPM specialist), Department of Environment, Ministry of Science, Technology and Environment, Government of **Nepal**	E: yubakgc@yahoo.com
Dr DevendraGauchan	Chief and Senior Scientist(Senior Agriculture Socio-economist), Socio-Economics and Agricultural Research Policy Division, NARC, Khumaltar, Lalitpur, **Nepal**	E: devendragauchan@yahoo.co.uk; dgauchan11@gmail.com
Dr Anand Kumar Gautam	Chief and Senior Scientist (Agronomy and crop modeler) Agri-Environment Unit, NARC, Khumaltar, Lalitpur, **Nepal**	E: akgrrp@rediffmail.com; aerd.narc@gmail.com
Mr SumanPantha	Jr Sub-editor, Kantipur Television Network,Kantipur Complex, PO Box 7368, Subdhanagar, Kathmandu, Nepal	E: sumanpantha6@gmail.com

Annexure 3: Presentations Website



ICRISAT Science with a human face — International Crops Research Institute for the Semi-Arid Tropics

AgMIP

South Asia Regional Research and Coordination Team Mid-Term Workshop

22-26 July 2013
Hotel Annapurna, Kathmandu, Nepal

List of Participants — Image Gallery

Monday, 22 July			
Welcome and Introductions, Workshop goals	Video	Presentation	Jim Jones
State of AgMIP	Video	Presentation	Cynthia Rosenzweig
Team presentations of goals, status of Fast Track, status and plans for full assessment			
Pakistan	Video	Presentation	Ashfaq Ahmad Chattha
Indo - Gangetic Basin	Video	Presentation	Subash N
Sri Lanka	Video	Presentation	Lareef Zubair, Nissanka S P
South Asia	Video	Presentation	Paramasivam P
SA Regional Coordination Team	Video	Presentation	Sumanthkumar V
Friday, 26 July			
Plenary Session: Goals for Day 5	Video		Cynthia Rosenzweig
Plenary Session: Participants present reports (45 min each)			
Pakistan	Video	Presentation	Ghulam Rasul
Indo Gangetic Basin	Video	Presentation	Subash N
Sri Lanka	Video	Presentation	Nissanka S P and team
South Asia	Video	Presentation	Geethalakshmi V
SA CRT	Video	Presentation	Dileepkumar Guntuku
Feedback from leadership, Discussion	Video		

© by ICRISAT. All rights reserved.

CGIAR A member of the CGIAR Consortium

http://ksiconnect.icrisat.org/wp-content/uploads/2013/08/AgMIP-Nepal.html

Annexure 4: FAQs

Climate Team FAQs

1) Which specific climate scenarios are required for core question simulation sets:

- RCP8.5
- Mid-Century
- Delta Scenario ('XA.AgMIP' in Climate Codes)
- 5 GCMs [CCSM4 (E), GFDL-ESM2M (I), HadGEM2-ES (K), MIROC5 (O), MPI-ESM-MR (R)]
- All farms

2) Why do we all use the same 5 GCMs?

- We are interested in consistency among regions and therefore require the same 5 GCMs to be used in all locations in Sub-Saharan Africa and South Asia.
- The 5 GCMs above were selected for their:
  - Widely used in recent assessments
  - Rigor of processes and resolution
  - Performance in monsoon regions

3) Will we assess the broader uncertainty of climate change projections?

- Yes, for 2 crop models, RCP8.5, Mid-Century

3a) Mean Changes Only

- 20 GCMs run only through crop/livestock model (no TOA runs)
- Delta Scenarios ('XA.AgMIP' in Climate Codes)
- 1 field: Best calibrated crop/livestock model location

3b) Mean and Variability Changes

- 20 GCMs run only through crop/livestock model (no TOA runs)
- Mean and Variability Scenarios ('XF.AgMIP' in Climate Codes)
- 1 field: Best calibrated crop/livestock model location

Crop/Livestock Model Team FAQs

1) How many crop/livestock models are needed for core question simulation sets?

- 2 crop models
- 1 livestock model (CLIPs)

2) How many crops/livestock are required for a given production system?

- At least one

3) What are the crop/livestock model components of the adaptation package?

- Regional Research Teams devise combination of adaptations represented in crop/livestock model parameters

Economic Model Team FAQs

1) Will we use a RAP for core question #1?

- No

2) What RAP will we use in core questions #2 and #3?

- Regional Research Teams are developing R1: Current Trends Continue

3) How will RAPs incorporate global and regional drivers?

- Begin with national-level drivers from global economic model
- Adjust to regional drivers
-

Information Technologies Team FAQs

1) How can we organize and execute large number of simulations?

- Core question crop/livestock runs at all farms: DOME
- Climate sensitivity runs at one location: Take experiment file (e.g., from QuadUI) for location and add 40 fields that each have different climate

2) Where will inputs, outputs, and products be archived?

- Utilize AgMIP data flow for Regional Integrated Assessments

Annexure 5: Mid-Term Workshop Checklist

This document provides a checklist that will help each team determine whether they are on track to produce all needed elements for the full examination of an integrated assessment at the July Mid-term Workshop. We will go through the entire integrated assessment for this single scenario in your integrated assessment region at the workshop, and then will develop a clear plan for the full assessment(s) going forward from the Midterm workshop to the end of the project (which will include additional elements). Details of these files and the associated methodologies are provided in the AgMIP Integrated Assessment Handbook (available at http://www.agmip.org/wp-content/uploads/2013/05/AgMIP-Regional-Research-Team-Handbook-v4.1.pdf)

Checklist – Climate Time Series Files

The .AgMIP file name is shown here to indicate that these files will need to be consistently formatted following the example in the AgMERRA dataset, and the naming convention detailed in the handbook also provides information about the specific files created. These will enable the full suite of crop modeling runs and agro-climatic analyses for the project.

Using New York City (USNY) as an example:

* **1.1 obtain AgMERRA estimated climate series for main weather location**
  first step: send an email to Alex (alexander.c.ruane@nasa.gov) with location's latitude, longitude, elevation, full name, and a 4-character code (e.g., USNY)
  file: **USNY0QXX.AgMIP**

* **1.2 combine with observations and quality control main weather station**
  first step: collect observations and calculate biases of AgMERRA time series. Fill in gaps using methodologies described in Section 4 of AgMIP Regional Integrated Assessment Handbook to achieve 1980-2010 daily file with all AgMIP variables.
  file: **USNY0XXX.AgMIP**

* **1.3 create CMIP5 GCM delta scenarios for Mid-Century (2040-2069) RCP8.5 using the CCSM4 global climate model scenario**
  first step: download CMIP5 datasets (meantasmax, meantasmin, meanpr, and lat/lon files) and Matlab/R scripts package
  file: **USNYIEXA.AgMIP**

Check List – Crop Modeling for Integrated Assessment

* **2.1** Document calibration of selected cultivar used (indicate experimental site, number of years, and type of experimental data used for calibration). Provide the cultivar genetic coefficients and evidence of calibration (simulated and observed anthesis and maturity with statistics, and graphical time-series if done). Provide model-ready input files.

* **2.2** Provide completed template spreadsheet (Survey_Data_Import file) of entered field survey data that includes all farmer fields.

* **2.3** Document source and identity of weather data used for farm survey simulations (including the weather used for simulating farm survey seasons, as well as the historical baseline weather (USNY0XXX.AgMIP), and the future climate scenarios (e.g., USNYIEFA.AgMIP). Also confirm that your weather files follow the AgMIP-scripting method and that the future climate scenario is for the correct time-slice and RCP).

* **2.4** Document source of soil profile information and provide soil profiles (either as separate page on the template spreadsheet, or as separate soil profile that can be viewed).

* **2.5** Provide Field Overlay files (DOME or DOMES) used to fill in missing information relative to the farm survey simulations. For example, that will give evidence for setting initial soil water, initial soil nitrate and ammonium, assumption for initial crop residue, stable soil C pool fraction, etc. This may require a short amount of explanatory text.

* **2.6** Provide the ACMO file with the simulated crop yield outputs for the matched farm yield survey fields, with explanation. Discuss causes for outliers in observed and simulated farm yields, *but as requested by economists, do not make any bias adjustments.*

* **2.7** Provide the ACMO file of successful 30-year simulations for baseline weather, for all farms (30 years per farm, show simulated yields for individual years, no averaging). Also provide Seasonal Strategy file (DOME) to provide sowing date rules and other assumed management information.

* **2.8** Provide the ACMO file of successful 30 year simulations for the appropriate identified climate scenario, for all farms (30 years per farm, show simulated yields for individual years, no averaging). This is for historical management without RAPS. This will require an additional Seasonal_Strategy file (DOME) to provide sowing date rules and other assumptions.

* **2.9** For adaptation simulations, provide Seasonal_Strategy file (DOME) with RAPS adaptations, sowing rules, and assumptions, along with ACMO file of 30 year simulations for climate change scenario with adaptation, for all farms (30 years per farm, show simulated yields for individual years, no averaging).

* **2.10** Provide evidence of interactions with economists on your team to confirm their understanding of the files and how to interpret crop modeling results, with yield distributions associated across farms in the matched survey case, and yield distributions associated with multiple weather years per individual farm.

Check List – Economics Team: TOA-MD Modeling

This checklist is to be used by RRT's economists for TOA-MD data preparation, model setup and results review. This checklist should be used for each scenario that is being modeled (i.e. Fast track, and adaptation scenarios).

DATA: Review data received from crop modelers and economic survey data

* **3.1** Make sure you received data from crop modelers in ACMO format

* **3.2** Check actual data for outliers, make histograms

* **3.3** Check simulated yields distributions

* **3.4** Correctly estimate relative yields and predicted future yields - Follow instructions provided on the updated Appendix 1 of the Handbook v4.1

* **3.5** Stratification: decide if stratification is needed/possible

* **3.6** Calculate statistics and double check they are correctly estimated (check predicted/modeled standard deviations, CVs) - Check again for outliers, strange values, etc

* **3.7** Make sure input parameters are consistent with scenario being modeled

* **3.8** Estimate and make sure RHO12 (correlation between returns in systems 1 and 2) makes sense

* **3.9** If needed, estimate and check values for correlations between returns to activities within systems (e.g. RHOC1, and RHOC2 for crops).

* **3.10** Use DATA and STUDY sheets to document the scenario that is being modeled.

MODEL Setup: Review key TOA-MD parameters and output data

* **3.11** Select the appropriate value for Do_Climate (Setup sheet)
* **3.12** Check units and select appropriate value for C_UNITS, L_UNITS, P_UNITS

* **3.13** Check units for CVs

* **3.14** Check STD_C, STD_L, STD_P: Standard deviation of net returns

* **3.15** Check activity Weights

* **3.16** Check fixed costs (are they needed?, enter correct values and check values for T1, T2 ,R)

* **3.17** Review all sheets making sure all the values are correct, consistent and in the correct places

Model Results:

* **3.18** Check output sheets for consistency

* **3.19** Check range of tradeoff points
* **3.20 Interpretation:** Review results to make sure they are consistent with economic theory and TOA-MD economic/statistical properties

Check List – Technical Stakeholder Engagement

The workshop includes engagement of at least one technical stakeholder (TS) per team for the first 1.5 days of sessions. This is owing to 1) A requirement by the funder (UK/DFID) to engage stakeholders broadly and across time; 2) Recognition that TS engagement is part of the underway work; and, 3) To ensure teams are not too far down the product line for a country before taking into consideration the likely areas of influence or need. The TS interactions should actually help to shape the work. Below we provide some criteria to help you in your selection of suitable TS. Teams should plan to have no fewer than two TS participating. AgMIP (HQ) will fund one, with the team funding the other.

* **4.1** TS works in one of the countries in your region

* **4.2** TS contributes technical expertise at a sub-national or national level

* **4.3** TS would likely benefit from exposure to the fuller AgMIP SSA representation

* **4.4** TS would likely engage in the technical discussion session on the afternoon of Day 1

* **4.5** TS would likely be interested and able to explore some RAPS-like work with your team in the morning of Day 2.

Team PIs will reach out to TS and provide information and full contact information also the Coordinating Research Team PI (Job or Dileep) with a copy also to agmip@columbia edu. AgMIP HQ will fund one TS for each team.

Annexure 6: FTP site naming conventions

1. CLIMATE

1.1 The merged historical period file (file name format: USNY0XXX.AgMIP). This come from historical observations merged with the MERRA-based data (bcMERRA is the same as AgMERRA), and should be complete from 1980-2010 with all variables and should not have any major outliers or physical discontinuities (e.g., Tmax < Tmin).

1.2 The historical period files for each farm in the region (e.g., if we had 12 farms around New York, we would have files name formats NY010XXX.AgMIP --> NY120XXX.AgMIP). These come from the agmip_farm2climate R scripts and the WorldClim data.

1.3 An example of the future climate data (from agmip_simple_delta.R and agmip_simple2full.R) from one GCM (use CCSM4 if you are looking for a first one to upload). File name format: NY01GEXA.AgMIP --> NY12GEXA.AgMIP

2. CROP

2.1. Crop model files for DSSAT (or XML for APSIM) documenting cultivar genetic coefficients used (provide experimental data for site used for calibration).

File name format: Files X, A, T, *.SOL, *.WTH, and *.CUL used for DSSAT models (in the standard DSSAT naming conventions), and the XML files for APSIM (with corresponding cultivar, management, soils, weather information in the APSIM naming conventions).

2.2. Field survey data entered. File name format: Survey_Data_Import-Region-Crop.csv

2.3. Field Overlay files (DOMES) used to fill in missing information for farm survey simulations. File name format: Field_Overlay_Region-Crop-Model.csv [Note: provide all (multiple) DOMES associated with the above Survey_Data_Import-Region-Crop.csv files]

For all the below ACMO files please use the following naming format:

ACMO-region-stratum-ClimID-RAPId-MgmtID-model.csv

For example

ACMO-Machakos-1-0XFX-0-0-DSSAT.csv for baseline,

ACMO-Machakos-1-MTFA-3-2-APSIM.csv for future conditions.

2.4. ACMO file with simulated crop yield outputs for the matched farm yield survey fields.

2.5. ACMO file of 30-year simulations for baseline weather, for all farms, with Seasonal Strategy file (DOME) for sowing rules and other assumed management information.

2.6. ACMO file of 30-year simulations for climate scenario, for all farms, with Seasonal Strategy file (DOME) for sowing rules and other assumed management information.

2.7. ACMO file of 30 year simulations for climate scenario with adaptation, with Seasonal_Strategy file (DOME) with RAPS adaptations, sowing rules, and assumptions.

3. ECONOMIC

3.1 Modeling:

- TOA-MD Input files (excel files). Use the TOA-MD data file name format: MD4data_YYYYY.xls (YYYY:Project identifier: team, region and scenario description)

- TOA-MD Output files (excel files). Use this TOA-MD output File name format: MD5_YYYY.xls

3.2 Reporting: use previously provided template to report results:

- RRTs FT-AD Report (PowerPoint and Excel files). Use the file name format of the templates provided and add the project identifier: YYYY_RRTs FT-AD Report.PPt and YYYY_RRTs FT-AD.xls

3.3 RAPs:

- DevRAP Matrix Use the DevRAP filename and add the Project identifier: YYYY_DevRAP.xls

- RAPs Documentation (based on template we distributed). Use this File name format: YYYY_RAPS Documentation.doc

- RAPs Presentation – Summary of RAPs narratives. Use this File name format: YYYY_RAPs Summary.PPT

Appendix 5

This page intentionally left blank

AgMIP The Agricultural Model Intercomparison and Improvement Project

REPORT

SUB-SAHARAN AFRICA
SOUTH ASIA

INTEGRATED ASSESSMENT RESULTS WORKSHOP

JANUARY 30 - FEBRUARY 4 2014
ARUSHA, TANZANIA

UKaid from the British people

CIAT 45 Centro Internacional de Agricultura Tropical / International Center for Tropical Agriculture

USDA

Report

Sub-Saharan Africa
South Asia

Integrated Assessment Results Workshop

January 30th – February 4th 2014

Acknowledgements

This workshop was made possible by support from UKAID and institutional support from CIAT. Organizational support was provided by J. Kihara, and Juliet Ogola, CIAT. This workshop report was prepared by J. Kihara with additional inputs from S. Lifson and C. Mutter. Thank you to AgMIP PIs and Leadership for their contributions to the program and planning and execution of the Workshop. Thank you also to the regional stakeholders for their generous time and participation.

Table of Contents

Introduction **3**
Day 1: Sharing Results **3**
Opening remarks 3
Workshop goals 5
Presentations by Regional Research Teams **5**
East Africa 5
Indo-Gangetic Basin 6
West Africa 6
Pakistan 6
Southern Africa 6
Sri-Lanka 7
Southern India 7
Southern Africa Livestock 7
SSA coordination team: 8
SA coordination team: 8
Organized media interviews 8
Afternoon of day 1: Disciplinary Breakouts **8**
Day 2: Refining Reports and Chapters **9**
Coordination meeting (Cross-region learning event) 9
Round robin discussions with leadership team 10
Day 3: Stakeholder Targeting Sessions **10**
Mid-day plenary 10
Dry-runs of stakeholder-targeted presentations 11
Day 4: Field Trip **11**
Day 5: Stakeholder Sessions **12**
DAY 6: Stakeholder Feedback **14**
Closing remarks 14
Appendix 1: AgMIP Stakeholders' Bio-data **16**
Appendix 2: AgMIP List of Participants **18**

Introduction

The AgMIP Finish line workshop held in Tanzania Arusha from January 30th - February 4, 2014 brought together 138 participants from 26 countries and six resource persons from the United States and Australia. The participants were from the eight regional AgMIP research teams. The research teams from AgMIP Sub-Saharan Africa (SSA) were East Africa (17 participants), West Africa (17), Southern Africa Livestock (10), Southern Africa (10), and the Sub-Saharan Africa Coordination team (7). The research teams from AgMIP South Asia were the Indo-Gangetic Basin South Asia (9), Southern India (4), Pakistan (13), Sri Lanka (10) and the South Asia Coordination team (6). The ratio of senior to young scientists was 4:6 for Sub Saharan Africa and 7:3 for South Asia. The young scholars of today will be the pool from which the scientific leaders of tomorrow will emerge. In addition, there were key members of the AgMIP leadership team, some invited speakers and 11 stakeholders that participated in the workshop (see appendix 1 on brief bio-data of stakeholders and appendix 2 on list of participants).

The objectives of the workshop were to:

1) Present results to other regional researchers, leaders, and stakeholders,

2) Incorporate feedback and finalize main results of Phase I report (ASA chapter and additional sections) and,

3) Ensure timely completion of project.

Day 1: Sharing Results

Opening remarks

Dr Saidou Koala made opening remarks on behalf of CIAT. He highlighted the need to be able to feed the world's growing human population that is expected to reach 8 billion by 2050. He mentioned AgMIP's approach of bringing together a multi-disciplinary community of scientists to improve the next generation of climate impact projections is in line with CIATs new strategy and in line with the CIAT-led CCAFS (Climate change, agriculture and food security) of the CGIAR. AgMIP, he said, is well-placed to indeed improve substantially the characterization of world food security due to climate change and to enhance adaptation capacity in both developing and developed countries addressing the challenge of improving the livelihoods of the growing populations. Dr Saidou mentioned that AgMIPs effort to build the capacity of local experts in its modeling efforts is of particular interest to CIAT since this will ensure that developing countries in SSA and SA have a critical mass for this type of activities. He re-iterated that it is indeed notable that AgMIP is:

a. Establishing teams of researchers with necessary skills to conduct these assessments in each of the participating countries by enhancing their capacity through training and hands on work
b. Adding value and making best use of available data

c. Providing an opportunity for the local researchers to work under the guidance and continuous support from a highly reputed and globally acknowledged team of scientists
d. Developing a good framework linking climate-crop-economic models to make comprehensive assessments of impacts both on crop productivity and economic well being
e. Developing a good platform that can be more extensively applied to cover the whole country or any target region and with flexibility to update with more up to date information
f. Is pioneering data publication and accessibility

He noted that AgMIP should keep in mind the small scale farmers who have seen their production systems become unreliable due to shifts in crop suitability, change in rainfall patterns and degrading soils as its target beneficiaries and, to inform policy makers and farmers alike on how to sustain production and productivity in the face of the climate change.

Dr Saidou Koala is the coordinator of the African Network for Soil Biology and Fertility (AfNet) of CIAT

Dr. Mboyi Mugendi, Zonal Director of Research and Development, Ministry of Agriculture, Food Security and Cooperatives, Northern Zone of Tanzania officially opened the AgMIP meeting. After some welcoming remarks, Dr. Mugendi said that:

"Agriculture is the single most important sector in the developing countries including Tanzania. About 80% of the population live in the rural areas of the developing world and earn their living through agriculture. Considering that the agricultural sector is powerful in reducing poverty, the importance of transforming the sector cannot be over emphasized.

Like many countries in the developing world, Tanzania has long history of good collaboration with institutions, such as CIMMYT, ICRISAT, CIAT in the area of agricultural research. The collaboration has resulted in the development and use of many technologies that have improved food security in the past years. However, these efforts are now constrained by climate change. Both sub-Sahara Africa and South Asia are the areas with the greatest risk. In Tanzania for example, farmers are already experiencing climate-related production challenges including:

i) Shifts in the onset of the rainy season,
ii) Drying of what were previously known as permanent marshlands,
iii) Changes in the amount and rainfall distribution,
iv) Disappearance of bimodal rainfall distribution,
v) Increasing temperatures contributing to changes in the agricultural productivity levels,
vi) Emerging of new crop diseases, such as the current Maize Lethal Necrotic Disease (MLND),
vii) Acute Malaria affecting farmers in highlands where the disease was not existing,

viii) Some adopted technologies such as date of seeding that is not working.

These challenges call for the need to clearly understand and inform policy makers on the best strategies of farming of the future, and to get farmers to adopt the right farming practices.

The implementation of *Agricultural Model Intercomparison and Improvement Project* (AgMIP) is timely and is a solution to the above mentioned challenges."

Dr. Mugendi commended AgMIP for its approach of integration, stakeholder engagement, capacity building and the results that have generated so far. Also, he indicated that for Eastern Africa, we could take advantage of the positive impacts of climate change, such as increased rainfall, citing an example of Dodoma region of Tanzania.

Workshop goals

Alex Ruane, AgMIP Science Coordinator, introduced the overall goals of the workshop. Participants were asked to incorporate any feedback received from peers and stakeholders and refine their reports and policy briefs. John Antle reminded the participants of the 3 key questions of AgMIP regional research teams (RRT).

Presentations by Regional Research Teams

Each RRT presented the results of their research. The following are the key highlights from the teams:

East Africa

Assessing the impacts of climate change in eastern Africa

Presenter: KPC RAO

Results from Kenya are more refined than other AgMIP East African (EA) countries. Climate data does not show differences in future seasonal rainfall or in the number of rainy days (>2mm) and there was no trend in the anomalies. The only observable trend is in the variability i.e., there is increasing coefficient of variation and also both minimum and maximum temperature increased over the years. Downscaled scenarios were in line with global predictions. Eastern Africa is getting wetter. Embu however is getting much wetter than it was projected globally. In one zone (LM4), there is a great difference between predictions with CO2 and without CO2. Agriculture Production Systems Simulator (APSIM) shows lower yield (and less variability) than in Decision Support System for Agrotechnology Transfer (DSSAT) where yields are also much higher. Response to fertilizer decreases with increasing temperature. Katumani variety is getting most adversely affected by the climate change due to its short duration nature. Uncertainties in the crop models are not translated into yields because there is no statistical difference in yields in Embu (across GCMs). Potential yield for the drier areas is decreasing (assuming no nutrient and water limitations).

Indo-Gangetic Basin

Strengthening simulation approaches for understanding, projecting and managing climate risks in stress-prone environments across central and eastern Indo-Gangetic basin

Presenter: Nataraja Subash

Sensitivity of the models to CO2 differs between DSSAT and APSIM. There are wide variations of percent gainers under different climate scenarios. The translation tool (Quadui) can be improved for automatic change of management practices such as sowing dates. Quadui is also creating large (megabites) APSIM simulation files and this also needs to be improved. Forced maturity due to crop stress without adaptation, as opposed to with adaptation could be the reason of the variations in gainers under different climate scenarios.

West Africa

Climate Change Impacts on West African Agriculture (CHIWARA)

Presenter: Sibiry Traore

Results for 3 sites (Nioro, Navrongo and Koutiala) were presented. In Nioro, three general circulation models (GCM) predict decrease and one increase while in Navrongo, one GCM predicts decrease and 3 increases. There are larger temperature increases in the southern parts of West Africa. Decreases in yields are predicted for all cereals in Nioro, while there is little change in Koutiala and Navrongo. Peanut yields are not affected by the climate change. There is much more sensitivity to climate change (temperature) in DSSAT than APSIM, except for peanut. Results show homogenization of model results across the GCMs. Percent gainers increase significantly as adaptation options are applied, but there is need to look into an expected strong effect of cash crops in future. APSIM is more sensitive to drought/moisture effects.

Pakistan

Impact of climate change on rice-wheat cropping system of Pakistan

Presenter: Ashfaq Ahmad

Soil related issues are key challenge in this system, as is terminal heat stress in wheat. Rainfall is decreasing towards southern Punjab. Sowing 15 days earlier can help to avoid the high mid-march temperatures in Punjab.

Southern Africa

Agricultural Model Intercomparison and Improvement Project (SAAMIIP)

Presenter: Yacob Beleste

There are a higher percentage of gainers with adaptation than without adaptation. There is increase in rainfall and temperature variability with climate change. There will be significant gain in maize production when there is positive development pathways (+ve RAP) and with adaptation.

Sri-Lanka

Modeling the impact of climate change on rice farming systems in NW Sri-Lanka

Presenter: Lareef Zubair

DSSAT predicts lower yield than APSIM for Yala site. Sensitivity to temperature is much more significant than CO_2 and rainfall. One adaptation option is to change from long to shorter duration varieties.

Southern India

Integrated assessment of climate change impacts on principal crops and farm household incomes in Southern India

Presenter: Paramasivan Ponnusany

The percentage of gainers declined across all GCMs from the near, mid and late century. Gainers are lower at high (8.5) than at low (4.5) GHG concentration scenarios. Both rainfall and temperature are on the increasing trend. APSIM predicted lower yields than DSSAT for the baseline. All GCMs show positive yield changes.

Southern Africa Livestock

Crop-livestock intensification in the face of climate change: exploring opportunities to reduce risk and increase resilience in Southern Africa using an integrated multi-modeling approach (CLIP)

Presenter: Patricia Masikate

There is an over prediction of milk production. Suggestions were made for the need for diversification as opposed to pushing intensification systems that may not work.

Following the RRT presentations, a general question was how to communicate results to other people when models do not agree, as observed for DSSAT and APSIM. There are residual differences in the models that indicate we do not know everything about the models, but there are also artefacts that can be corrected to reduce some of the disagreements.

SSA coordination team:

Presenter: Job Kihara

Presented work on synthesizing and sharing knowledge across regional research teams in SSA.

SA coordination team:

Presenter: Dileep Guntuku

Showed tools designed and developed for information sharing and capacity building including KSIConnect and AgEd Open courseWare (AgED) and open data repositories.

Organized media interviews

Media present at the opening of the meeting included Tanzania broadcasting corporation (TBC), the Guardian newspaper, and radio. Selected participants interviewed included Dr. Lucas Mugendi (Zonal Director), Dr. John Antle (AgMIP leadership), Dr. KPC Rao (Principal investigator, AgMIP eastern Africa) and Dr. Job Kihara (AgMIP SSA coordination). Media publications from these interviews are highly circulated and can be found for the Guardian (31st January 2014) and DailyNews (4th February 2014).

Afternoon of day 1: Disciplinary Breakouts

Charge to disciplinary breakouts was given by Alex Ruane and John Antle.

Crop team breakout:

The agenda was:

1) To get impressions of the crop results from other teams,

2) Know what has been done to understand model results (e.g. sensitivity analyses),

3) Gain lessons on adaptation from other teams,

4) Discuss pending tasks for the final template,

5) Discuss methodological challenges/problems being experienced and

6) Develop action plans for the RRT.

The team discussed some possible model parameterization and functions that need to be checked/evaluated as plausible reasons to explain the source of model prediction differences. This could include soil parameters, carbon pools, vapour pressure deficits, nitrogen and water stresses. Understanding how different models simulate at the same soil layers is important, as

is the simulation of fertilizers. Sensitivity analysis helps point to possible sources of model differences, but this is not the only method.

The need to document how the models were tweaked was emphasized, including documentation of the data used for the model calibrations. It was also noted that it is important to document the DSSAT and APSIM model versions since some of the older versions differ e.g. in CO_2 sensitivity to newer versions.

Day 2: Refining Reports and Chapters

Day 2 and 3 were devoted to teams working on refining their models, reports and ASA chapters. There was re-analysis of data by some teams, e.g. SAAMIIP to try and find out reasons for variability/uncertainty. During this time, the two coordination teams from SSA and SA held a joint learning event.

Coordination meeting (Cross-region learning event)

Teams planned on video recording of plenary reporting sessions to supplement the PowerPoint presentations. The coordination teams identified the need to coordinate learning across teams and regions (SA vs. SSA). This is to take advantage of the different levels of expertise in analysis and presentation of economic data for example. As such, there is not much sharing of tools such as R codes for graphing, etc. across teams and this needs to be encouraged/catalysed. This is a nice way of supporting team reports.

The SSA coordination team can borrow ideas on information and communication technology (ICT) from SA coordination team which is having an AgED open course for agriculture and allied subjects where, through agreements, the online training materials can be hosted. SSA team will consider whether to use the Webex service or adopt the SAs KSI connect that uses Adobe Connect without the need to install add-ins to access, and where time delays are handled by keeping a copy of the videos of the livestream.

There are recurrent debates on what is the difference between APSIM and DSSAT with regard to how they handle different cases. Coordination teams, through modelling expertise of the SSA coordination team, can prepare materials with a local flavour that can be translated into video or a cartoon by SA ICT team, with input from the more experienced AgMIP modellers. Another material on this line would be in support of AgMIP results presentation and interpretation. We see a lot of potential to utilize the diversity of the SSA and SA coordination teams' expertise to move AgMIP forward.

Being close to the teams will help understand their needs better. Although there are some "single points" of contact e.g. in the SA case, there is need for a budget for coordination principle investigators (PIs) to visit RRTs during key events such as national stakeholder meetings.

The coordination teams noted the need for strategic communication for impact and the channels/medium have to be well planned. This communication should be in simple illustrations and in local languages (where needed). It was not clear yet what help is needed by the RRTs from the regional coordination teams (RCTs) on this, including in generation of policy briefs.

Both SA and SSA have quite similar future plans for capacity building including short-term courses or internships where students come to learn special skills in a residence set-up to fulfil AgMIP's research agenda (SA and SSA). Training in AgMIP will continue to be demand-driven and modules targeted to the specific needs. A key concern arising from SSA coordination team and coincidentally from Peter Craufurd was the need to know what the coordination led training is contributing to the capacity of the persons trained. Following this, a tool was quickly prepared and responded to by 78 participants of the Arusha workshop. Other members will be reached through Survey Monkey.

Round robin discussions with leadership team

Different RRTs held separate discussions with the leadership group. Teams were provided some feedback on their book chapter, the expected reporting and timelines for the project.

Day 3: Stakeholder Targeting Sessions

Logistics for field trip were introduced followed by the agenda for the day. RRTs continued with their breakouts. The coordination teams held discussions on their publications, future engagement in AgMIP, final reporting etc.

Mid-day plenary

What have we learned from global crop-economic model comparisons in AgMIP? Presenter: Herman Lotze-Campen

Regional results for SSA on the above topic were presented. Key questions were the future of agricultural prices, evolution of agricultural production and how these will be affected by climate change in the future. Some models (3) showed price decreases by 2050 but other models had price increases. Wheat in SSA showed some differences in exogenous yield changes but there are greater differences when considering the effective yield change (following endogenous adjustments). Open issues for AgMIP global economics for the second phase were provided/ suggested such as representation of the different land types. Interaction across scales, considering the drivers and assessing consistency across the scales was highlighted. The work presented is consistent to AgMIP's RRTs focus of what would the economy be like with and without climate change. What have not been considered in the global economics are the adaptation strategies to mitigate climate change. The models differ in how they treat different aspects hence the variations in prices. An observation was made that there is worry of double

accounting for the highly aggregated global models when we add trends on data that is derived from adaptations, e.g. where fertilizer has been applied.

Stakeholder identification and need matching in AgMIP: what to consider

Presenter: Joske Houtkamp

Engagement of stakeholders requires boundary skills to facilitate dialogue between research and practice. Stakeholder identification and selection are based on power-interest dimensions, proximity to the project, information needs of each stakeholder at different spatial/regional scales etc. For AgMIP and going to the next level of identification of stakeholders, we need more insights into how to engage the stakeholders at the various levels, understand their responses etc. and a framework for doing this would be nice. Also, meeting stakeholder requirements without going astray is important. It is a constant struggle to find the match between project and stakeholder needs but we have to continue as we perfect our boundary work skills.

Dry-runs of stakeholder-targeted presentations

RRTs presented slides developed with key messages for stakeholders. A few lessons or comments on the stakeholder targeted presentations included need to make visual illustrations of some of the results (double channel communication with numbers and visuals), reduce technicality of some of the graphs, give a final wrap-up slide with main conclusions. Posing also a few questions that can get stakeholders thinking of what next was praised.

Day 4: Field Trip

The trip involved a travel to Mount Kilimanjaro region to appreciate the farming systems. At the first stop, participants interacted and discussed with farmers on their practices in production of maize, cabbages and sunflower under irrigation systems. At the second stop, participants appreciated the design, intensity and complexity of the Chagga home gardens including the aging farming community, the mining of nutrients from lowlands among others.

Day 5: Stakeholder Sessions

Stakeholders representing Pakistan, Botswana (SAAMIIP), Kenya (AgMIP EA), Zimbabwe (Clip), and India participated. John Antle introduced to these stakeholders the goals of AgMIP and the need of AgMIP to derive and communicate climate change impact on agriculture results relevant for policy. Making science useful to stakeholders is a communication challenge posed to the stakeholders to help AgMIP find the best ways to create impact through better interpretation, visualization and presenting. After each of the invited stakeholders gave remarks pointing to their roles and the key climate change-related challenges in their countries and regions, RRT PIs presented the key messages designed for the stakeholders. Stakeholders then gave the following as responses to the presentations.

> Messages must be tailored to the target; whether farmers or policy makers, grassroots level etc. these grassroots don't speak the language of graphs. They need "if you do a, b, c, you will increase your yields.

I. Presenting a positive outlook is nice to provide hope and not doom to the people. Need to take into account drastic/extreme events that may be part of the future climate despite no change in mean rainfall and or temperature. An important question remaining is "What will be the critical point at which the high potential areas (projected at present not to be affected badly by climate change) will become vulnerable or stop being productive. Taking into account differences in c3 or c4 plants would be nice as they may react different to climate change. More representation of farmers' needs and opinions may be needed.
II. To what extent are farmers willing to change to adopt the range of options that are available (or presented)? This will require participatory action research, working with farmers to identify the different constraints and opportunities they would want to seize. Participatory visioning would also help. Farmers are concerned about profitability of the options so this should be captured.
III. As we look at changes in rainfall and temperature, to what extent are we looking at changes in pest/diseases and their behaviours? These are difficult to measure and they have capacity to regulate to climate changes than crops.
IV. How would you communicate the uncertainty evident in your results to the stakeholders? Is crop insurance one way of addressing this uncertainty problem for West Africa? Here, we could rely on probabilistic methods.
V. What are the strategies put forward in relation to livestock in ensuring the young generation becomes aware and start to adapt to climate change? The stakeholder involvement process is one step and in the next phase, we will engage more with stakeholders for this knowledge to reach the users.
VI. Most of our modelling is based on inorganic fertilizers, but are these sustainable? We need to include organic fertilizers as well since we might get answers on sustainability (i.e., compare and provide with the best future adaptation). AgMIP has tested only very

few adaptation options. For making recommendations, we need a range of options that farmers can choose from.

VII. The fusion of farmer concerns, scientists and policy makers is a key challenge for linking science and practice.

VIII. We need to see messages highlighting the role of stakeholders and policy in addressing the negative activities contributing to climate change (e.g., activities even external to agricultural sector).

IX. Many farmers want a solution for their problem today but in AgMIP we are talking of 2050, which may not be very interesting for the farmer today.

X. Decisions on whether to discourage production of certain crops that consume more water, such as rice and sugarcane are needed for certain production environments. Pulses such as mung bean and pigeon peas are coming up as alternatives for income. Cereal-based cropping systems highly impact the water-balance and soil health so introducing other varieties/crops (green maturing crops) will improve these.

XI. We have to talk to stakeholders at all levels to develop comprehensive adaptation packages. We have to ask ourselves what we do with the losers reported in our economic analyses? Should they remain as losers or are there alternatives we can offer for these?

XII. At the Arusha meeting, AgMIP had more results and more confidence that it needed stakeholders to indicate the importance, interpretation and presentation of these results.

Small meeting with stakeholders: the importance of stakeholders was introduced and the need for their involvement in AgMIP. Persona-scenario technique was introduced and the stakeholders were requested to create a fictitious person and what that person needs, for what purpose and when, i.e., a detailed requirement of information for this persona is to be created and for AgMIP, we will have different personas. Persona is a short story of identities to help our researchers start to appreciate what kind of users they are targeting.

In RRT breakouts, scientists engaged with stakeholders from their region to discuss the following questions:

I. What are the adaptations needed?

II. What should teams do to influence stakeholders?

III. What timescales and, matching policy to timescales (farmers short-term, infrastructure long-term).

IV. What are the key messages that the teams should focus on for policy-makers?

V. What can stakeholders do to promote research, be an advocate of the program and the regional teams?

VI. Provide feedback & advice to teams on the interaction with policy-makers and with regard to presentations & policy briefs.

VII. How to speak the language of stakeholders and in this case, indicate some direct benefits of AgMIP work for farmers.

"A good policy should start addressing issues of now, before the medium and long-term timescales"—Stephen Kinguyu

We need to quantify the benefits of adaptation vis-à-vis not taking action. Also, agriculture should be addressed in terms of its linkages with other sectors such as water management and management of other resources. Adaptation strategies should be targeted to small and large-scale farmers who make up the farming community in southern Africa. On its part, the CIWARA team agreed that the most important stakeholders are the farmers. Current research can help identify the most vulnerable farmers so that policymakers can make plans to help those categories, to minimize climate-related risks. There is need to involve farmers associations and bring one or two to workshops as *personas*.

"Advice from stakeholders is keep the messages simple, link strategies to the livelihoods and show the gains" and,

"Farmers don't listen, farmers want to see."

We need to expand our locations to validate the results. The capacity building of the researchers and other stakeholders is important. Food value chain development is needed.

DAY 6: Stakeholder Feedback

Goals of the day as introduced by John Antle were (1) the incorporation of stakeholder feedback into analyses, reports and publications, 2) finalizing work plans to close of project and (3) separate discussions (for economists and crop scientists) on uniformity and presentation of ASA chapter results. The RRTs then went into breakout sessions for the rest of the morning.

In plenary, the RRTs presented themes for policy briefs that highlighted issues such as socio-economic transformations, adaptations, projected climate changes, policy changes and recommendations. For adaptation, these could, depending on region, include early/late maturing varieties/crops, heat/drought, pest/diseases tolerances, and diversifications of cropping systems. Climate change effects are on systems so there is need for cross-sectorial/holistic approaches. Also, more thought needs to be given to addressing or communicating uncertainty or data with large degrees of uncertainty.

Closing remarks

Inclusion of livestock was good, capacity building was applauded, and continuous improvements where "AgMIP flying plane under construction." In the future, CLIP will include rangelands and effects of temperature on animals. CIWARA, despite challenges of multiple

institutions, had a lot of capacity built and AgMIP lessons will be used in other projects in West Africa. For Pakistan group, AgMIP developed capacity in novel research in the most upfront frontiers of climate change. The team has learned a lot about stakeholder interactions and working together. In the future, they will introduce new crops in the mixed cropping systems, and want to add the livestock component as well. The Pakistan group will be pleased to host a kick-off of second phase. PI foresees a regional centre established for the whole of south Asia region. Indo Gangetic Basin RRT benefited with capacity building e.g. through boot camps, have understood regional integrated assessments, and in the last six months have started integrated farming systems modelling. In future, the team would like to include livestock-crop interaction modelling. They will need resources to collect new AgMIP survey data. South India RRT has found AgMIP to be a truly integrated multi-disciplinary project. SAAMIIP reiterated the capacity building that started in some cases from scratch (some scientists without prior exposure to some models). Challenges for internet-based learning sessions were encountered due to connectivity problem. AgMIP EA observed the challenge of data quality coming from national partners.

Remarks by AgMIP leadership: Cynthia Rosenzweig reiterated the need to focus on extreme climate event analysis to understand trends, variability and change in the regions. The leaders appreciated the efforts made by the teams in realizing AgMIP Phase1 results and encouraged them to continue, especially on the area of stakeholder interactions to transfer this useful knowledge and results to impacts, and making data accessible within the project.

Appendix 1: AgMIP Stakeholders' Bio-data

Dr. K. Veeranjaneyulu is the University Librarian & Professor and Head i/c., University Computer Centre at Acharya N.G. Ranga Agricultural University, Hyderabad and CCPI, e-Granth project. He has two and half decades of professional experience. He holds M.Com, MLISc, BGL and Ph.D. from S.V. University, Tirupati. He also possesses PGDLAN and a diploma in Software Applications. He has organized several workshops, seminars, conferences and training programmes in the field of Library and Information Science. Ten candidates were awarded M.Phil. degrees under his guidance. Currently he is guiding eight Ph. D. students. He is a resource person to various Academic Staff Colleges in the country. He has delivered many guest lectures at universities in Andhra Pradesh, Maharashtra, Tamilnadu, Karanataka and Haryana. He has organized more than 20 conferences, seminars, workshops and training programmes for working Librarians, Information Specialists, Teachers and Students and attended nearly 12 training programmes.

Dr. K D. Kokate was educated in Karnal, Haryana, India. He started his scientific career from Arid Desert Region (Jodhpur), worked in Temperate High Hills (Shimla), Scarcity Zone (Dhule), Coastal Peninsular Zone (Dapoli) and Western Region of Maharashtra State (Rahuri) in India. At present, he is looking after one of the largest and unique Technology Application Systems in the World having more than 10,000 scientific and technical staff in 637 Krishi Vigyan Kendras (KVKs)/ Agriculture Science Centres across the country. As Deputy Director General (Agricultural Extension), ICAR, since 2009, his contributions include reforms in technology application, market linkages, synergy and partnership with key stakeholders, ICT application for Knowledge management via mobile-based Farmer Advisory and e-linkage Connectivity to Eight Zonal Project Directors (ZPDs) and 192 KVKs across India, contingent crop planning for drought mitigation, organizing programs for sustaining yield of various crops, technologies related to climate resilient agriculture and advisory to 1.3 million farmers.

Professor Iqrar Ahmad Khan holds B.Sc. and M.Sc. from University of Agriculture, Faisalabad, Pakistan and M.Sc. and PhD from University of California, Riverside, USA. He has supervised more than 100 postgraduate students and involved in over 30 research and development projects.

Dr. Arvind Kumar has distinct professional experience of 39 years involving teaching/research/extension activities in various capacities in India. He was the principal Investigator of Oilseed Project, which developed 40 varieties of oilseed Brassica suited for different agro-climatic zone since 2002, leading to increase in production from 5.1 million tonnes in 2001-02 to all time high (8.2 million tonnes in 2010-11). Project Leader of Hybrid Project – Rapeseed-Mustard, funded by NATP, leading to development of first mustard hybrid based on Mori Cytoplasmic Male Sterility system. Dr. Kumar guided 31 PG Research Projects including 9 for Ph.D. degree programs.

Eng. Ananda Weerasinghe has worked in the area of water resources management for the Mahaweli Authority of Sri Lanka for 40 years with a focus on the North-Western and neighbouring regions of Sri Lanka for 25 years. He has been engaged with farmers, in helping set up pioneering farmer organizations, water management panels at the local scale and in overseeing comprehensive services for farmers in the river basin authority's command areas in Kurunegala and Anuradhapura districts. He is a corporate member of the Institution of Incorporated Engineers in Sri Lanka and holds an M.B.A from Wayamba University of Sri Lanka.

Dr. H. Malleshappa belongs to the Indian Forest Service, 1985 Batch, Tamil Nadu Cadre. He holds a Post Graduate in Agriculture from University of Agricultural Sciences, Bangalore and has completed his inter-disciplinary Doctoral studies in Agriculture and Biodiversity. As a Deputy Conservator of Forests he has undertaken many Soil Conservation, Afforestation assignments. Currently he is the Director of Environment and is in charge of preparation of the State Action Plan on Climate Change (SAPCC).

Shakwaanande Natai is the Head of Environment Management Unit at the Ministry of Agriculture Food Security and Cooperatives (MAFC), Tanzania. She holds a Master of Science in Soil Science and land Management from Sokoine University of Agriculture, Morogoro, Tanzania. She is responsible for monitoring compliance with the Environmental Management Act (EMA Cap 191, Tanzania) in the Agricultural Sector. She also conducts, monitoring and overseeing Environmental Impact Assessment (EIA) and Strategic Environmental Assessment (SEA) in Agricultural Projects and Programs.

Manzoor A. Khan holds B.Sc. and M.Sc. in Agri-Economics from Punjab University, Paksitan. He served in various West African projects as a World Bank chief Agronomist. He was also involved in other World Bank funded projects, namely water resource conservation and development, rural infrastructure, new cropping system and techniques, education of rural communities, skill gap analyses and training of members of the local civil service officials. He is a permanent member of the international panel of consultants with the World Bank.

Stephen Mutua KING'UYU holds B.Sc. and M.Sc. from the University of Nairobi, Kenya. He is Agriculture Deputy Director – Adaptation and Mitigation at the National Climate Change Secretariat, Ministry of Environment, Water & Natural Resources. His responsibilities include: the domestication of conventions and protocols related to climate change adaptation and mitigation and coordination of the relevant national policy processes. He also coordinates efforts to mainstream climate change in the medium-term plan (MTP) for the implementation of Kenya's Vision 2030 and the climate-proofing of the Vision 2030 flagship projects.

Dumisani Mbikwa Nyoni holds BSc (honours) agriculture, animal science and M.Sc. agricultural extension. He is the provincial agricultural extension officer in the department of

agricultural technical and extension services responsible for overseeing the provision of extension services and farmer training, development and dissemination of agricultural technologies and information, provision of technical and advisory services which includes food security monitoring, facilitate compliance with legal and policy measures including migrant pest control, coordination of agricultural programs, management of human, assets and financial resources to achieve set targets.

Appendix 2: AgMIP List of Participants

Name	Organization
East Africa Team	
Frank J. Wambura	Tanzania Meteorological Agency & Ardhi University, Dar-es-Salaam, Tanzania
Siza Tumbo	Professor & AgMIP PI-Tanzania, Sokoine University of Agriculture, Morogoro, Tanzania
Sixbert K. Mourice	Faculty Member, Sokoine University of Agriculture, Morogoro,Tanzania
Barnabas Msongaleli	Lecturer, Sokoine University of Agriculture, Morogoro, Tanzania
Ibrahim Kadigi	Researcher, Sokoine University of Agriculture, Morogoro, Tanzania
Girma Mamo	Agrometeorologist, Ethiopian Inst. of Agric. Research (EIAR), Adema, Ethiopia
Robel Takele	Ethiopian Inst. of Agric. Research (EIAR), Ethiopia
Fikadu Getachew	Ethiopian Institute of Agric. Research (EIAR), Ethiopia
K.P.C. Rao	Principal Scientist and Country Representative & PI AgMIP EA, ICRISAT, Addis Ababa, Ethiopia
G. Sridhar	Manager, Project Finance & MIS, Finance Dept. ICRISAT, Addis Ababa, Ethiopia
Richard Mulwa	University of Nairobi, Nairobi, Kenya
Mary N. Kilavi	Principal Meteorologist, Kenya Meteorological Service, Nairobi, Kenya;
Majaliwa-Mwanjalolo	Associate Professor, Makerere University, Kampala, Uganda;
Carolyn Nandozi	Research Assistant, Makerere University, Kampala, Uganda
Nampijja Josephine	Student, Makerere University, Kampala, Uganda
Bonabana Jackline	Makerere University, Uganda
Musinguzi Patrick	Asst. Lecturer, Makerere University, Kampala, Uganda
West Africa Team	
MacCarthy, Dilys, S	Research fellow, University of Ghana, Accra, Ghana
Bright Salah Freduah	Research Assistant, SIREC University of Ghana, Kpong, Accra, Ghana
Stephen Narh	SIREC College of Agriculture, University of Ghana, Legon, Ghana
Eric Koomson	Research Assistant, Department of Soil Science, University of Ghana, Accra, Ghana
Evelyn Asante-Yeboah	Research Assistant, University of Ghana, SIREC, Accra, Ghana
Joseph Amikuzuno	Agro-Economist, University of Development Studies, Tamale, Ghana
Ibrahima Hathie	Director of Research, IPAR, Dakar, Senegal
Agali Alhassane	Agronomist - Crop Modeler, AGRHYMET Regional Center, Niamey, Niger
Seydou B. Traore	Agro-Meteorologist, AGRHYMET Regional Center, Niamey, Niger
Pierre Sibiry Traore	Remote Sensing Scientist, Bamako, Mali
Akinseye, Folorunso M.	Research Scholars, ICRISAT, Bamako, Mali
Madina Diancoumba	ICRISAT, Bamako, Mali
Fatondji Dougbedji	Ing. Agronome Scientist, ICRISAT, Niamey, Niger

Sissoko, Manda	Scientific Officer, ICRISAT, Bamako, Mali
Tiganadaba Lodoun	INERA, Ouagadougou, Burkina Faso
Sanon Moussa	Senior Research Officer, INERA, Ouagadougou, Burkina Faso
Jon Lizaso	Professor, Technical University of Madrid (UPM), Spain
Southern Africa Livestock Team	
Patricia Masikati	Post Doc Fellow, ICRISAT, Bulawayo, Zimbabwe
Sabine Homann-Kee Tui	ICRISAT, Bulawayo, Zimbabwe
Sue Walker	Theme Leader/Programme Director, Univ. of Free State, South Africa & Crops for Future Res. Centre, UNMC Jalan Broga, Semenyih, Malaysia
Lieven Claessens	Principal Scientist Natural Resources, ICRISAT/Wageningen University, Nairobi, Kenya
Sebastiao Famba	Lecturer, Universidad Eduardo Mondlane, Maputo, Mozambique
Christopher Lennard	Climate Scientist, University of Cape Town, Cape Town, South Africa
Arthur Gama Chibwana	Lilongwe University of Agriculture and Natural Resources, Bunda College of Agriculture, Lilongwe, Malawi
Sisito Givious	Principal Research Officer/Modeler, DR & SS, Bulawayo, Zimbabwe
Katrien Descheemaeker	Alterra Wageningen UR, Netherlands
Southern Africa Team	
Yacob Beletse	PI-AgMIP Southern Africa, Agricultural Research Council- Roodeplaat VOPI (ARC), Pretoria, South Africa
Olivier Crespo	Research Officer, University of Cape Town, South Africa
Willtrud Durand	Researcher, ARC Grain Crops Institute, Potchefstroom, South Africa
Charles Nhemachena	Senior Research Specialist, Human Sciences Resource Council, Pretoria, South Africa
Mduduzi Sunshine Gamedze	Co-PI AgMIP SAAMIP, University of Free State, Box 339, Bloemfontein, South Africa
Mogos Teweldemedhin	Polytechnic of Namibia, Namibia
Patrick Gwimbi	Lecturer, National University of Lesotho, Roma, Lesotho
Thembeka Mpuisang	Lecturer, Botswana College of Agriculture, Gaborone, Botswana
Weldemichael Tesfuhuney	University of Free State, South Africa
Matthew Jones	SASRI, South Africa
Indo-Gangetic Basin Team	
Subash Natarajа Pillai	PDFSR, Uttar Pradesh, India
Harbir Singh	Principal Scientist & Co-PI AgMIP, Project Directorat for Farming Systems Research (PDFSR), Uttar Pradesh, India
Balwinder Singh	CIMMYT, New Delhi, India
Dinesh Babu Thapa Magar	Agricultural Scientist, Socio-economics and Agri Res. Policy Div.(SARPOD), Nepal Agric. Res. Council (NARC), Kathmandu, Nepal
Gokul Prasad Paudel	Socio-Economist, CIMMYT SARO, Kathmandu, Nepal
Rajendra Daral	Senior Scientist, National grain Legumes Res. Program, Nepal Agricultural Research Council (NARC), Narayangarch, Chitwan, Nepal
Md. Abeed Hossain Chowdhury	Director (Computer & GIS), Bangladesh Agric. Res. Council (BARC), Farmgate, Dhaka, Bangladesh
Mohammad Kamrul Hasan	Principal Scientific Officer, Bangladesh Agric. Res. Institute (BARI), Bangladesh
Sk. Ghulam Hussain	Soils Expert & Crop Modeler, Center for Env. Geog. Info. Services, Bangladesh Agric. Res. Council (BARC), Dhaka, Bangladesh

South India Team	
Paramasivam Ponnusamy	Professor, Tamil Nadu Agricultural University (TNAU), Coimbatore, India
D. Raji Reddy	Director of Extension, ANGR Agricultural University, Andhra Pradesh, India
Sreenivas Gade	Principal Scientist, ANGR Agricultural University, Hyderabad, Andhra Pradesh, India
Pakistan Team	
Ashfaq Ahmad Chatta	Lead PI AgMIP Pakistan, University of Agriculture, Faisalabad, Pakistan
Muhammad Ashfaq	Institute of Agric. and Res. Economis, University of Agric., Faisalabad, Pakistan
Syed Aftab Wajid	Co-PI AgMIP Pakistan, University of Agriculture, Faisalabad, Pakistan
Tasneem Khaliq	Co-PI AgMIP Pakistan, University of Agriculture, Faisalabad, Pakistan
Jamshad Hussain	University of Agric., Faisalabad, Pakistan
Irfan Ahmad Baig	Asst. Professor, University of Arid Agriculture, Faisalabad, Rawalpindi, Pakistan
Syed Asif Ali Naqvi	Research Officer, University of Agriculture, Faisalabad, Pakistan
Muhammad Sohail Akhtar	Research Assistant, University of Agriculture, Faisalabad, Pakistan
Ahsan Raza Sattar	Co-PI AgMIP Pakistan, University of Agriculture, Faisalabad, Pakistan
Syed Ahsan Ali Bokari	Electrical Engineer (Climate Team) Pakistan Meteorological Dept., Islamabad, Pakistan
Shakeel Ahmad	Associate Professor & Co-PI AgMIP Pakistan, Bahauddin Zakariya Univerity (BZU), Multan, Punjab, Pakistan
Wajid Nasim	Co-PI AgMIP Pakistan, COMSATS Institute of Information Technology (CIIT), Vehari, Pakistan;
Ghulan Rasul	AgMIP Pakistan
South Asia Coordination Team	
Dileepkumar Guntuku	AgMIP South Asia Coordination & Global Leader, ICRISAT-Patancheru, Andhra Pradesh, India
Rosana P Mula	Coordinator, ICRISAT-Patancheru, India
Piara Singh	Consultant (Crop modeling), MIP, ICRISAT-Patancheru, Andhra Pradesh, India
Venkata Venigalla Sumanth Kumar	Scientist, ICRISAT-Patancheru, India
Chukka Srinivasa Rao	Senior Manager - Data Management, ICRISAT-Patancheru, Hyderabad, India
Dakshina Murthy Kadiyala	Scientist, ICRISAT-Patancheru, Hyderabad, India
Sri Lanka Team	
Lareef Zubair	Foundation for Environment, Climate &Technology (FECT), Rajawella Sri Lanka
A.S.M. Prabodha Malinga Bandara Agalawatte	Research Scientist, Foundation for Environment, Climate &Technology (FECT), Rajawella, Sri Lanka
Dumindu Indika Herath	Research Scientist, Foundation for Environment, Climate &Technology (FECT), Rajawella, Sri Lanka
Samsudeen Zeenas Yahiya	Social Scientsit, Foundation for Environment, Climate &Technology (FECT), Rajawella, Sri Lanka
Kariyawasam Don Nandasiri Weerasinghe	Chair Professor, Faculty of Agriculture, University of Ruhuna, Mapalana, Kamburnpitiya, Sri Lanka
Sarath Premalal Nissanka	Administrative Leader of AgMIP-Sri Lanka, University of Peradeniya, Peradeniya, Sri Lanka
Wijayasiri M. Weerakoon	Director, Field Crop Research and Development Institute, Department of Agriculture, Mahailluppallama, Sri Lanka
Ahsa Sajeewani Karunaratne	Senior Lecturer, University of Sabaragamuwa, Belihuloya, Sri Lanka
Rasnayaka M. Herath	Agricultural Economist, SEPC, Department of Agriculture, Peradeniya, Sri Lanka
Janaka Gunaratne	Senior Lecturer, Crop Science/Climate, Faculty of Agriculture, Rajarata University, Mihintale, Anuradhepura, Sri Lanka

AgMIP Leadership Group	
PIs:	
Jim Jones (via video)	University of Florida, USA
Cynthia Rosenzweig (via video)	Goddard Inst. For Space Studies Goddard Inst. for Space Studies, New York, USA
John Antle	Oregon State University, USA
Teams:	
Alexander Ruane	NASA, GISS, New York, USA
Roberto Valdivia	Oregon State University, USA
Peter Thorburn	AgMIP Crop Co-Leader, CSIRO, Brisbane, Australia
Kenneth Boote	University of Florida, USA
John Hargreaves	CSIRO, Brisbane, Australia
Cheryl Porter	AgMIP IT Team, Co-Lead, University of Florida, Gainesville, USA
Christopher Villalobos	IT Coordinator, University of Florida, Gainesville, USA
Peter Craufurd	CIMMYT-Nairobi
Hermann Lotze-Campen	Dept. Head, Agric. Economist, Potsdam Institute for Climate Impact Research, Germany
Resource Persons:	
Gerrit Hoogenboom	Washington State University, USA
Sonali McDermid	Columbia University, USA
Daniel Wallach	INRA, Toulouse, France
Guillermo Baigorria	University of Nebraska-Lincoln, USA
Ioannis Athanasiadis	Democritus University of Thrace, Greece
Davide Cammarano	Postdoctoral, University of Florida, Gainesville, USA
Coordination:	
Carolyn Mutter	Columbia University, USA
Shari Lynn Lifson	Columbia University, USA
Participants:	
Caleb Dickson	Oregon State University, USA
Joske Houtkamp	Researcher, Alterra Wageningen UR, The Netherlands
Rolf Sommer	Senior Scientist, CIAT, Nairobi, Kenya
Evan Girvetz	Senior Scientist, CIAT, Nairobi, Kenya
Isaac Savini	Research Officer, CIAT, Nairobi, Kenya
Sub-Saharan Africa Coordination	
Job Kihara	PI-AgMIP Regional Coordination (KEMIC), CIAT, Nairobi, Kenya
Saidou Koala	Senior Scientist & AfNet Coordinator, CIAT, Nairobi, Kenya
Andre Bationo	Senior Soil Scientist & AgMIP Stakeholders facilitator, AGRA, Accra, Ghana
Charles L. Vanya	Meteorologist, Dept. of Climate Change and Meteorological Services, Malawi
Stakeholders	
Arvind Kumar	Dep. Director General (Education), Pusa, New Delhi, India
Olaotswe Kgosikomato	Department of Agricultural Research, Gaborone, Botswana
Stephen Kung'uyu	Coordinator, KCCAP, Min. of Environment, Nairobi, Kenya
Dumisani Mbikwa Nyoni	Dep. Director, Dept. of Agric. Tech. & Extension Services, Buylawayo, Zimbabwe
Shakwaanande Natal	Head of Env. Mgnt Unit, Min of Agric., Dar-es-Salaam, Tanzania
Kiran D. Kokate	Dep. Dirctor General, ICAR, New Delhi, India
K Veeranjaneyulu	Professor & University Librarian, ANGR Agricultural University, Hyderabad, India
Manzoor Ahmad Khan	Farmer & Retired World Bank Chief Agronomist, Lahore, Pakistan
Ijaz Munir	Secretary to the Govt. of the Punjab, Agriculture Department, Lahore, Pakistan
Anandakithsiri Weerasinghe	Eng. Project Manager, Hydrodynamics Consultancy, Mahaiyawa, Kandy, Sri Lanka
Iqrar Ahmad Khan	Professor of Horticulture and Vice Chancellor, University of Agriculture, Faisalabad, Pakistan

Index

adaptation, 5, 7, 11, 12, 20, 28, 31, 62–70, 75, 98, 116–122, 145, 150–153, 180, 181, 188–192, 252–255, 271, 276, 300, 308–310, 320, 347
Africa, 7, 9, 14, 16
AgMERRA, 30
APSIM, Agricultural Production Systems Simulator, 15, 19, 79, 81, 92, 93, 121
Australia, 393

beans, 84
biotic stresses, 95
Botswana, 125
Brazil, 355–374
    agricultural climatic risk zones, 358
    climate change impacts, 358
    data and climate models, 361
    regional climate models, RCMs, 364
Burkina Faso, 25

cash crop, 84
cereal farming, 31
China, 375–390
    adaptation strategies, 387
    climate change challenges, 25, 375
    climate impacts on agricultural production, 376
    future climate impacts, 378
    integrated assessment results, 385
CIWARA, climate change impacts on West African agriculture, 25–72
climate, 3, 7, 28, 33, 47, 76, 122
climate change, 4, 9, 42, 49, 84, 88
climate change impacts, 4, 7, 45–61, 71, 76, 85, 99–116, 147–150, 182–188, 245–252, 271–275, 303–308, 339–345
climate change scenarios, 28, 42, 64, 88, 99
climate-smart agriculture, 13
CLIP, Crop–Livestock Intensification in the Face of Climate Change Project, 159–198
coffee, 79, 84
Consultative Group of International Agricultural Research (CGIAR), 4, 16
crop–livestock systems, 7, 83
crop modeling training courses, 393–408
    approaches followed, 396
    course syllabus, 400
    experiences during the course, 403
    history, 394
    instructors, 399
    planning and preparations, 399
    train-the-trainers, 399
crop models, 7, 37–40, 41, 43, 49, 76, 88, 90–95, 121, 139–144, 171–174, 231–239, 266–269, 289–297, 326–329
    crop model calibration, 37, 93, 94, 139–143, 171, 234–237, 266, 291, 292, 326, 327
crop phenology, 49
crop residues, 30
crop varieties, 37, 84
crop yields, 49, 62, 94, 95
cropping systems, 79

data, 18, 19
development, 43, 84
droughts, 27
DSSAT, Decision Support System for Agrotechnology Transfer, 79, 81, 92, 93, 99, 121

early-warning systems, 122
East Africa, 19, 75–122
    adaptation package, 98

climate change challenges, 75
data and methods of study, 85
soil and climate, 79–81, 86–88, 90, 92–95
farming system, 77
settings and locations, 77, 78
impact of climate change on crop production, 99
representative agricultural pathways (RAPs), 84
stakeholder interactions, 84
Economic Community of West African States (ECOWAS), 14
economic models, 7
El Niño Southern Oscillation (ENSO), 4
Ethiopia, 75, 78
evapotranspiration, 49
extreme events, 27

fertilizers, 39, 43, 90, 97
food security, 122
France, 315

genetic coefficients, 40
Ghana, 16, 25, 28, 33, 46, 47, 49, 57, 62, 63
Greece, 75
greenhouse gases (GHGs), 5
global climate models (GCMs), 5, 28

heat tolerance, 42, 43

incomes, 57, 70
India, 201, 259, 281
Indo–Gangetic Basin (IGB), 259–278
adaption, 271
climate and soil data, 261
climate change impacts, 271
farming system investigated, 262
settings and locations, 261
representative agricultural pathways (RAPs), 264, 270
stakeholder interactions, 261
infrastructure, 32
International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), 15
Intertropical Convergence Zone (ITCZ), 4
irrigation, 43

Köppen–Geiger climate classification, 5
Kenya, 75, 77, 79, 85, 97, 159

land tenure, 5
legumes, 30
Lesotho, 125
livelihoods, 5
livestock, 30, 79, 150, 159–195

maize, 31, 37, 42, 45, 46, 84, 92, 99, 104
Malawi, 5
Malaysia, 125, 159
Mali, 25
management, 5, 90, 98
Mann–Kendall tau-b non-parametric function, 87
millet, 31, 37, 63
models, 15, 18, 37, 365
multiple models, 19, 42, 393
Mozambique, 159

Namibia, 125
National Agriculture Research institutes (NARs), 4
natural resources, 27
Netherlands, 159
Niger, 25
non-agricultural income, 56
non-governmental organizations (NGOs), 31

peanut, 31, 46, 47, 64
per capita income, 57
pests, 95
plant population, 90
policies, 10, 28, 122
poverty, 5, 55, 56, 65, 77, 78

rainfall, 19, 78, 83, 100
regional integrated assessments (RIAs), 3, 4, 8, 10, 28, 30, 121
representative agricultural pathways (RAPs), 4, 84, 97
root distribution, 45

Sahel, 4, 37
SAAMIIP, Southern Africa Agricultural Model Intercomparison and Improvement Project, 125–157
seed technologies, 33
Senegal, 25, 27, 28, 41, 42, 46, 47, 53, 62–64, 70
sentinel sites, 18
Sierra Leone, 27

smallholder farming systems, 27, 30, 76, 77, 122
soil organic carbon (SOC), 37
soil organic matter (SOM), 27
soil surveys, 37, 81, 82
sorghum, 84
South Africa, 125, 159
South Asia, 201–215
  adaption, 271, 276
  capacity building, 214
  climate change, 272
  climate change impacts, 259
  data management, 214
  extended monsoon scenarios, 213
    data and methods of study, 264, 266, 270
    farming system investigated, 261, 262
    representative agricultural pathways (RAPs), 264
    sensitivity of current agricultural production systems to climate change, 273
    stakeholder interactions, 263
  Pakistan, 201, 206, 219–256
    climate, 220
    cropping systems, 221
    evaluation of potential adaptation strategies, 250
    impacts of climate change on future agricultural production systems, 248
    interaction with stakeholders, 242
    outreach activities, 242
    previous studies, 221
    representative agricultural pathways (RAPs), 244
    rice–wheat cropping system, 224, 225, 227, 229, 231–239
    sensitivity of current agricultural production systems to climate change, 245
  private sector, 33
  representative agricultural pathways (RAPs), 210
  South India, 281–312
    adaptation package, 300
    agroeconomic assessment, 297
    benefits of climate change adaptations, 308
    climate change challenges, 281, 282
    climate change impacts, 305
    climate data and scenarios, 287
    crop modeling, 289
    data and methods of study, 286
    integrated assessment results, 302
    interactions with stakeholders, 284
    maize-based farming system, 283
    representative agricultural pathways (RAPs), 284, 298
    sensitivity of current agricultural production systems to climate change, 303
  Sri Lanka, 315–348
    adaptation strategies, 320
    changes in varietal use, 348
    climate change challenges, 315
    climate data, 323
    climate results, 330
    crop data, 324
    crop model calibration, 326
    crop model simulations, 328
    crop modeling results, 333
    data for integrated assessment, 325
    farmer perceptions of climate change, 320
    integrated assessment, 329, 339, 345
    interactions with stakeholders, 319
    key decisions, 320
    methods of study, 325
    national policymaking, 320
    representative agricultural pathways (RAPs), 321
    water management, 348
Southern Africa, 125–198
  adaptation, 146,150, 180, 181, 188–191
  climate change challenges, 127–130
  climate change impacts, 160–162
  data and methods of study, 137–145, 167, 168, 170, 171, 173, 175, 176
    crop–livestock farming systems, 163–165
    settings and locations, 162
  economic impact of climate change on crop production, 148
  farming system investigated, 130–134
  impact of climate change on crop production, 147, 182, 183, 185, 187
  representative agricultural pathways (RAPs), 137, 146, 166, 178, 180
  stakeholder interactions, 136, 165
Spain, 25

stakeholders, 10, 11, 13, 17, 31, 84, 136, 165, 209, 211, 212, 242, 263, 284, 319
Sub-Saharan Africa (SSA), 3
  capacity building, 14
  communication, 16
  data limitations, 17
  integrated assessment, 4
  regional contrasts, 19
  stakeholder engagement, 10, 13, 14
  training, 15, 16

temperature, 6, 26, 31, 33, 37, 38, 94
Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD), 7, 43, 105, 130, 144, 176, 209, 241, 264, 286, 329
training, 15, 16, 87, 393

uncertainty, 13
USA, 75, 125, 159, 201, 219, 259, 281, 315, 355, 393

variability, 62, 64, 80, 82
vulnerability, 75

water, 82
weeds, 95
West Africa, 15, 19, 25–72
  adaptation, 43, 62
  climate change impacts, 25, 27, 45, 47, 49, 55, 56
  data and methods of study, 33
  farming system investigated, 28
    climate and soil data, 28
    settings and locations, 28
  representative agricultural pathways (RAPs), 31, 43
  stakeholder interactions, 31
WorldClim climate database, 28

Zimbabwe, 5, 159